



上海交通大学
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扩散模型：方法与应用

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* 部分素材取自朱军教授、李崇轩教授关于扩散模型的报告



背景：生成式AI正迅速发展

Midjourney V5创建高分辨率的逼真图像



Prompt: kids party favors

<https://legacy.midjourney.com/showcase/recent/>



Prompt: sand and water in a desert, in the style of metropolis meets nature, les nabis, majestic ports, national geographic photo, tangled nests, dark emerald and beige, aerial view



Prompt: film still of 16 year old blond girl. looks like alice in wonderland. wearing modern clothes designed by Alexander McQueen, balancing joyously but happy. Extremely detailed and realistic. colorful garden. sharp focus. in london. Directed by Tony McNamara



背景：生成式AI正迅速发展

DALL·E 3直接理解复杂的自然语言指令



I am doing a report on cirrus clouds for my high school science class. I need photorealistic images that show off how wispy they are. I am going to compare them to photos I took of puffy cumulonimbus clouds at my house yesterday.



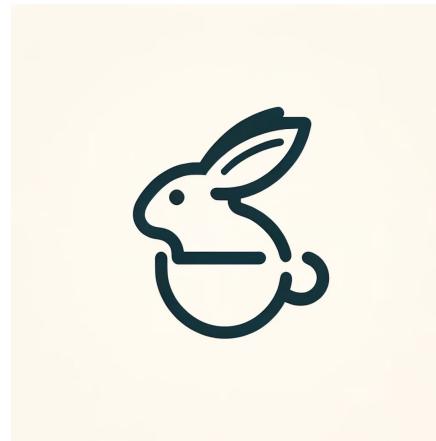
Here are the photorealistic images of cirrus clouds showcasing their wispy and delicate nature. You can compare these with the photos of cumulonimbus clouds you took to highlight the differences in their structures and appearances. If you need any further information or assistance, please let me know!



My business partner and I are creating a coffee shop inspired by our mutual love for rabbits. We have a logo we like a lot that is minimalist with a rabbit, but anxious to get your take on it.



Here are some minimalist rabbit-inspired logo designs for your coffee shop. Each captures the essence of a rabbit while integrating coffee-related elements. I hope these designs align with the vision you and your business partner have for your coffee shop. If you have any feedback or further preferences, please let me know!



I am working with a web designer for a new website to sell bicycle helmets. Could you recommend a few website UI's that are both modern and simple that I can share with her as examples?



Here are some website UI designs tailored for selling bicycle helmets with a modern and simple aesthetic:





背景：生成式AI正迅速发展

视频生成



Pika 1.0 by Pika Labs



Gen-2 by Runway

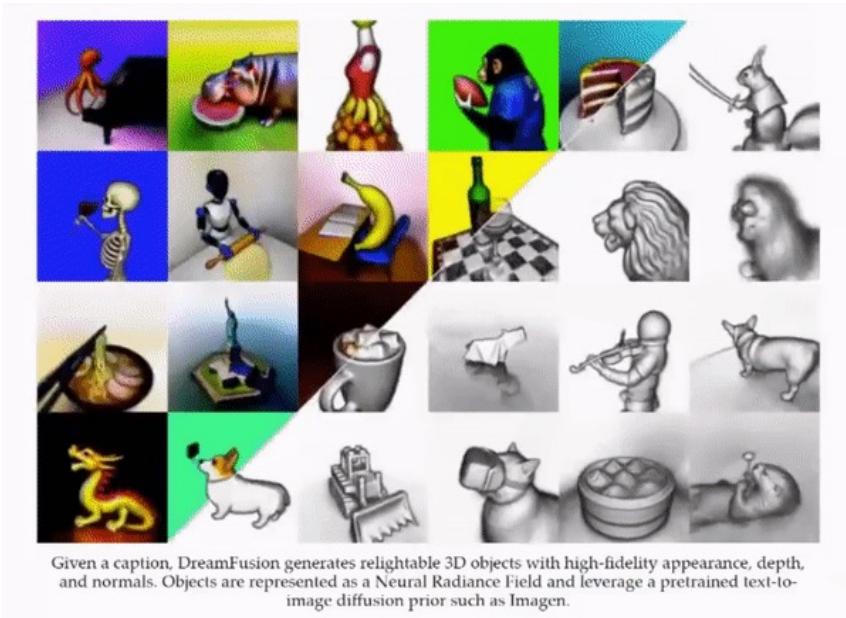
Prompt: the late afternoon sun peeking through the window of a New York City loft



W.A.L.T

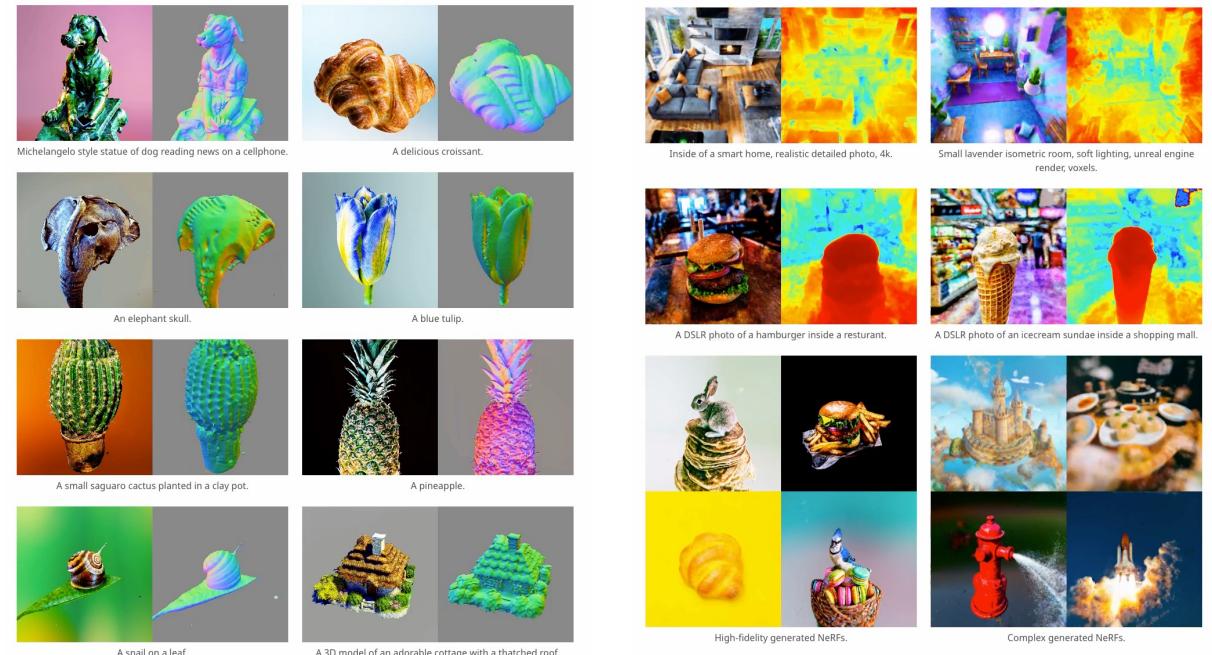


背景：生成式AI正迅速发展 3D内容生成



DreamFusion by Google

<https://dreamfusion3d.github.io/index.html>; <https://ml.cs.tsinghua.edu.cn/prolificdreamer/>



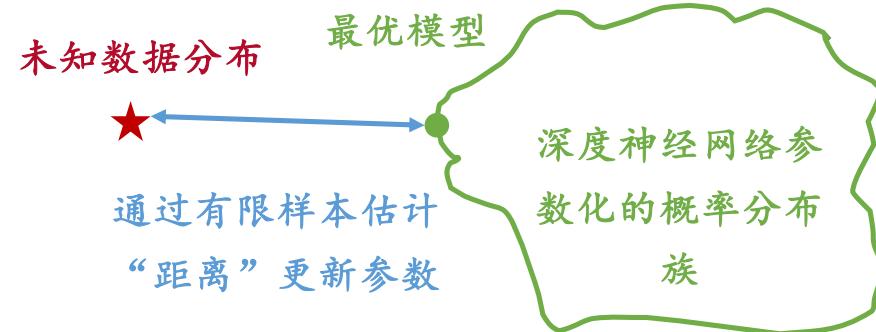
ProlificDreamer by Tsinghua



背景：生成式AI的内核

深度生成模型

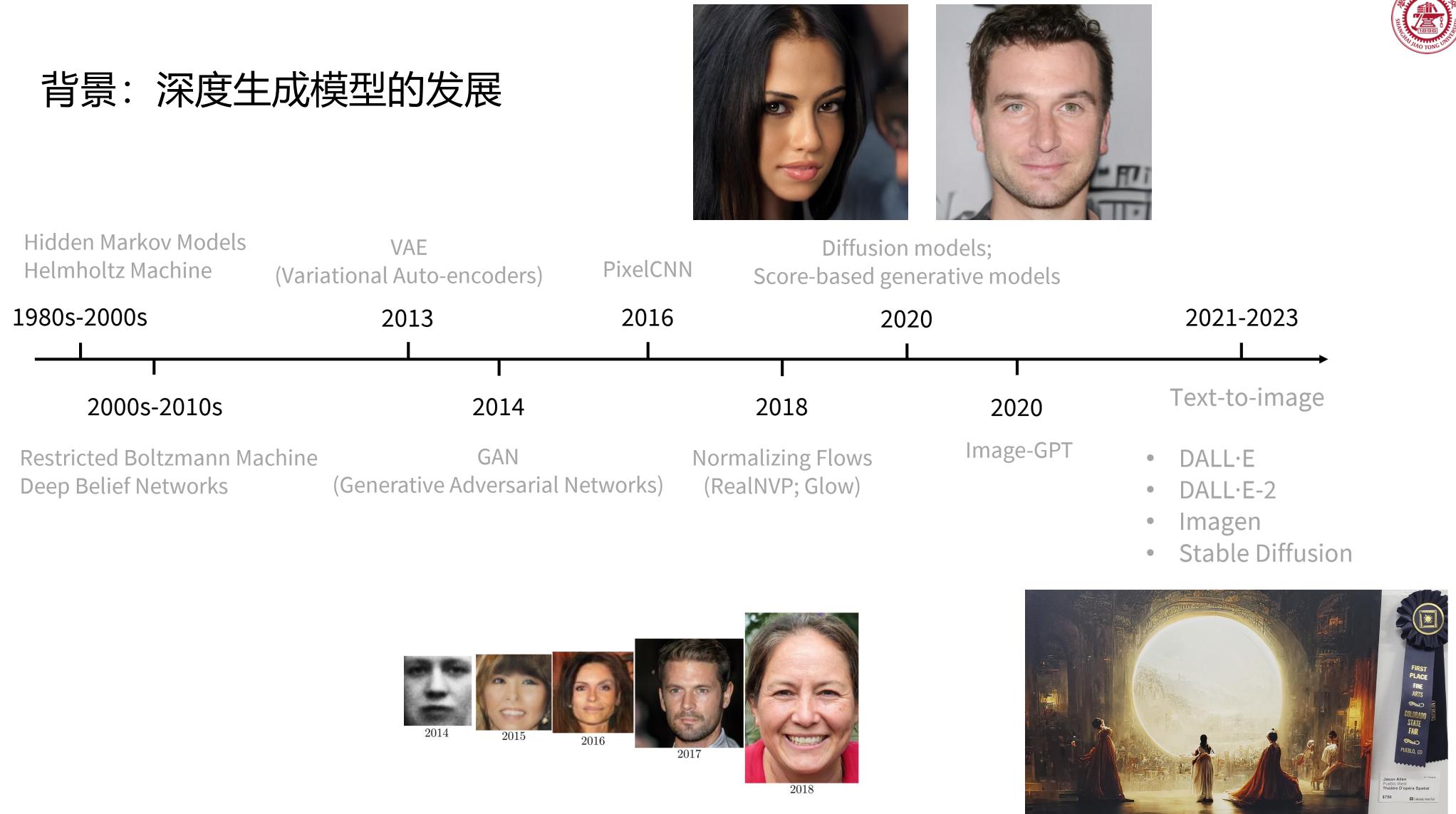
- 核心问题：高维、复杂的联合概率分布的表示、学习与推断



经典图像数据：超过十万维的多峰分布



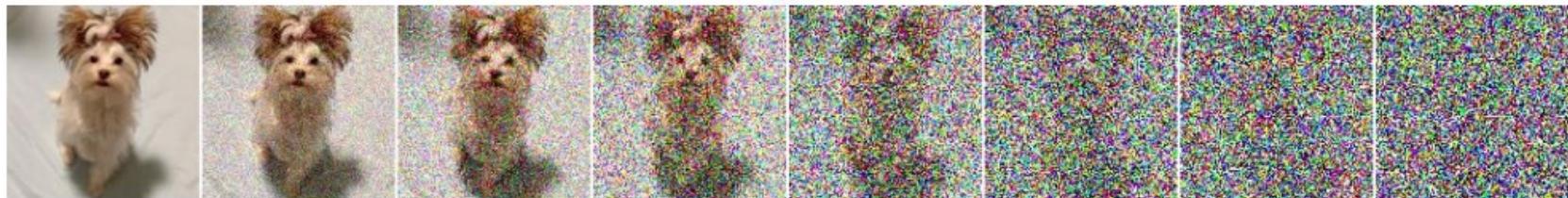
背景：深度生成模型的发展





扩散模型的定义：加噪

前项链：高斯核马尔科夫链，一般 1000 步



数据分布

$$q(\mathbf{x}^{(0)})$$



高斯噪声

加入噪声

$$q(\mathbf{x}^{(T)}) \approx \mathcal{N}(\mathbf{x}^{(T)}; 0, \mathbf{I})$$

转移概率

$$q(\mathbf{x}^{(t)} | \mathbf{x}^{(t-1)}) = \mathcal{N}(\mathbf{x}^{(t)}; \mathbf{x}^{(t-1)} \sqrt{1 - \beta_t}, \mathbf{I}\beta_t)$$

Sohl-Dickstein et al., Deep unsupervised learning using nonequilibrium thermodynamics. ICML 2015

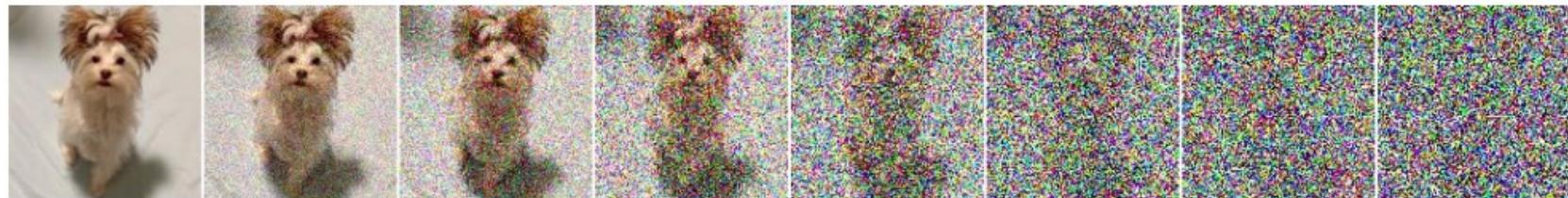
Ho et al. Denoising diffusion probabilistic models (DDPM), NeurIPS 2020

Song et al. Score-based generative modeling through stochastic differential equations, ICLR 2021



扩散模型的学习：去噪

可学习的反向高斯核马尔科夫链



模型分布

$$p(\mathbf{x}^{(0)}) \approx q(\mathbf{x}^{(0)})$$



高斯先验分布

$$p(\mathbf{x}^{(T)}) = \mathcal{N}(\mathbf{x}^{(T)}; \mathbf{0}, \mathbf{I})$$

参数化转移概率

$$p(\mathbf{x}^{(t-1)} | \mathbf{x}^{(t)}) = \mathcal{N}(\mathbf{x}^{(t-1)}; f_{\mu}(\mathbf{x}^{(t)}, t), f_{\Sigma}(\mathbf{x}^{(t)}, t))$$

时间共享参数的神经网络作为高斯核，如何学习模型参数？



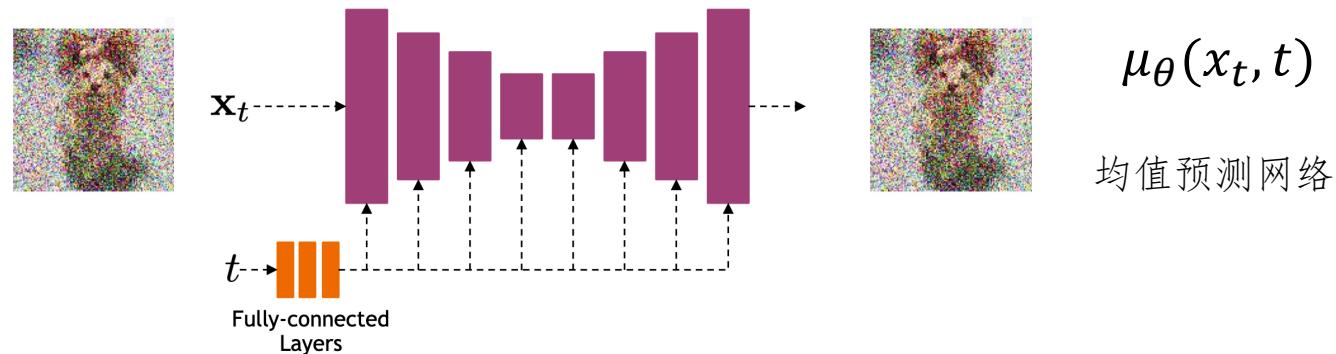
扩散模型的学习目标：最大似然估计

层次化隐变量模型 (**hierarchical VAEs**) , $p(x_0) = \int p(x_0|x_1)p(x_1|x_2)\dots p(x_T)dx_{1\dots T}$

=> 最大化变分下界:

$$\mathbb{E}_{q(x_0)}[\log p_\theta(x_0)] \geq \mathbb{E}_{q(x_0)}\mathbb{E}_{q(x_{1:T}|x_0)} \log \frac{p_\theta(x_{0:T})}{q(x_{1:T}|x_0)} \approx \mathbb{E}_{p_D(x_0), \epsilon} \mathbb{E}_{t \sim U[1,2,3\dots,T]} \|\mu_\theta(x_t, t) - \mu(x_t, x_0)\|^2$$

只预测均值，手工设置方差，例如对应前向分布噪声层级 $\beta_t I$ (对应特殊数据分布最优解)





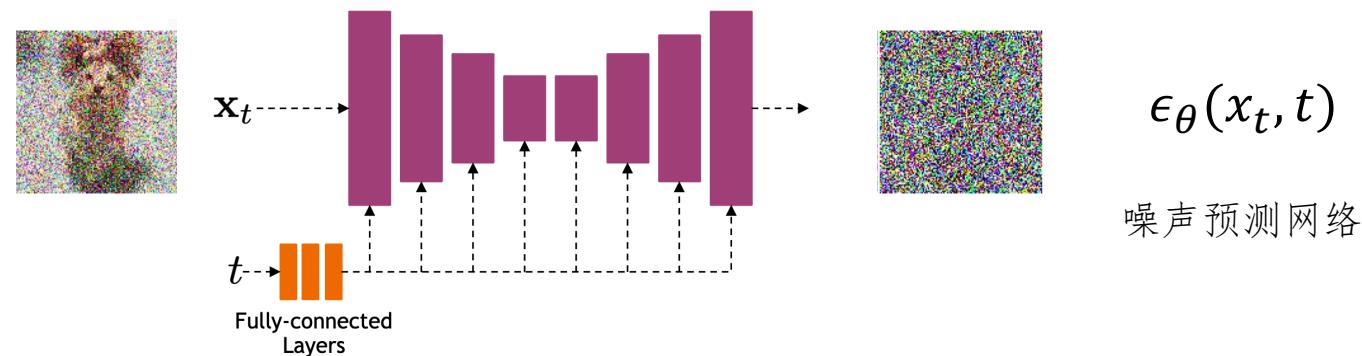
扩散模型的学习目标：噪声预测训练

均值回归等价于噪声回归： $\mu_\theta(\mathbf{x}_t, t) = \frac{1}{\sqrt{1 - \beta_t}} \left(\mathbf{x}_t - \frac{\beta_t}{\sqrt{1 - \alpha_t}} \epsilon_\theta(\mathbf{x}_t, t) \right)$

=>同时学习 1000 个噪声层级不同的去噪任务（可联系到 denoising score matching）

$$\|\mu_\theta(x_t, t) - \mu(x_t, x_0)\|^2 \Leftrightarrow \|\epsilon_\theta(x_t, t) - \epsilon\|^2$$

噪声预测网络 高斯噪声





扩散模型：算法

Algorithm 1 Training

```
1: repeat
2:    $\mathbf{x}_0 \sim q(\mathbf{x}_0)$ 
3:    $t \sim \text{Uniform}(\{1, \dots, T\})$ 
4:    $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
5:   Take gradient descent step on
      
$$\nabla_{\theta} \|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_{\theta}(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\epsilon}, t)\|^2$$

6: until converged
```

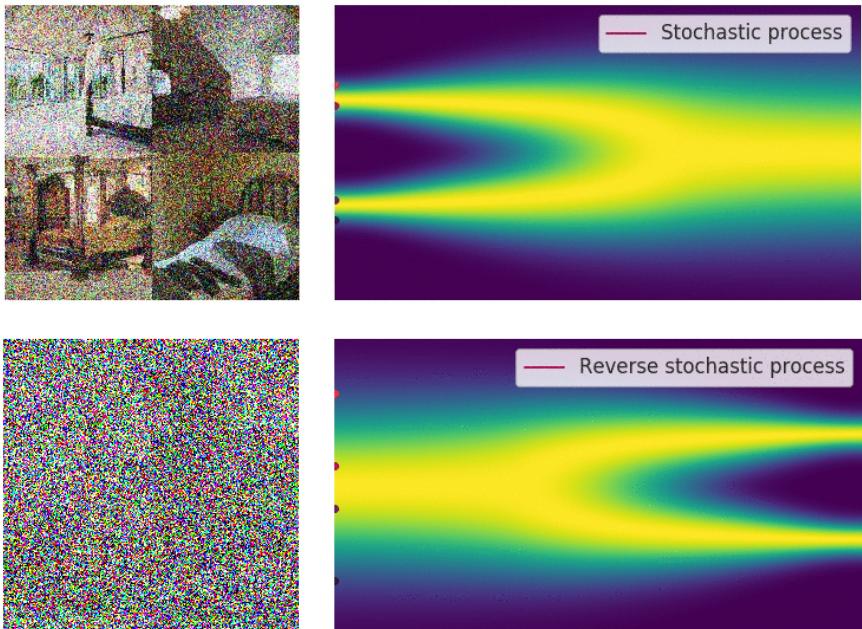
Algorithm 2 Sampling

```
1:  $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
2: for  $t = T, \dots, 1$  do
3:    $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
4:   
$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \boldsymbol{\epsilon}_{\theta}(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$$

5: end for
6: return  $\mathbf{x}_0$ 
```



连续时间扩散模型：无限步数



前向过程：

$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w}$$

反向过程：

score function

$$d\mathbf{x} = [\mathbf{f}(\mathbf{x}, t) - g^2(t)\nabla_{\mathbf{x}} \log p_t(\mathbf{x})] dt + g(t)d\bar{\mathbf{w}}$$

- 基于神经网络近似得分函数即可得到生成模型

训练目标：

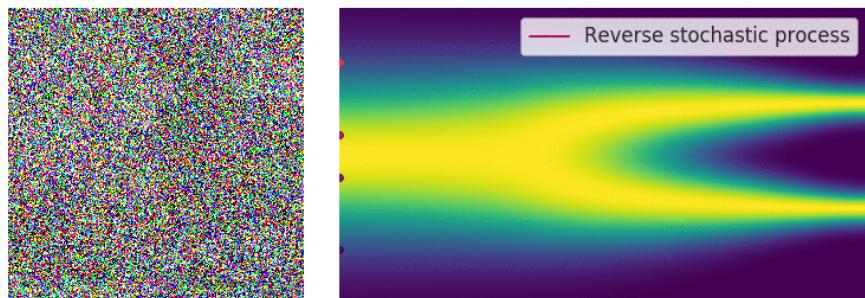
$$\mathbb{E}_{p_D(x_0), \epsilon} \mathbb{E}_{t \sim U[1, 2, 3, \dots, T]} \|\epsilon_\theta(x_t, t) - \epsilon\|^2$$

无限步
→

$$\frac{1}{2} \int_0^T \omega(t) \mathbb{E}_{q_0(\mathbf{x}_0)} \mathbb{E}_{q(\epsilon)} [\|\epsilon_\theta(\mathbf{x}_t, t) - \epsilon\|_2^2] dt$$



连续时间扩散模型：无限步数



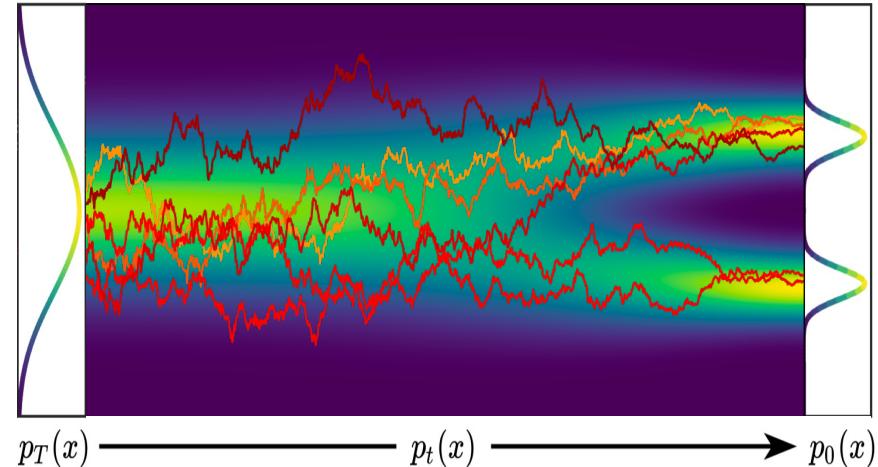
Diffusion SDE:

$$d\mathbf{x}_t = \left[f(t)\mathbf{x}_t + \frac{g^2(t)}{\sigma_t} \epsilon_\theta(\mathbf{x}_t, t) \right] dt + g(t)d\bar{w}_t, \quad \mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \tilde{\sigma}^2 \mathbf{I})$$

Diffusion ODE (Probability Flow ODE, 确定性, 边际分布一致) :

$$\frac{d\mathbf{x}_t}{dt} = f(t)\mathbf{x}_t + \frac{g^2(t)}{2\sigma_t} \epsilon_\theta(\mathbf{x}_t, t), \quad \mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \tilde{\sigma}^2 \mathbf{I})$$

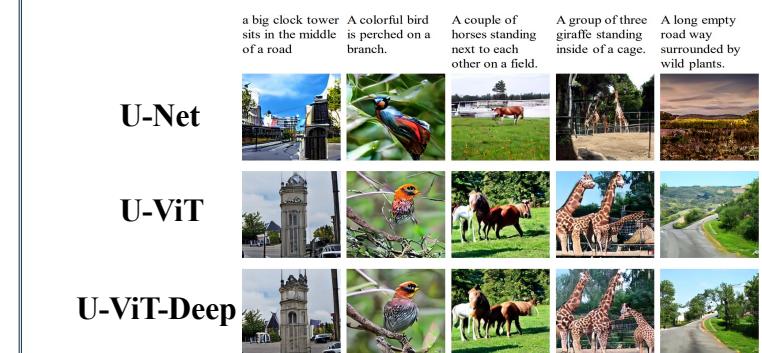
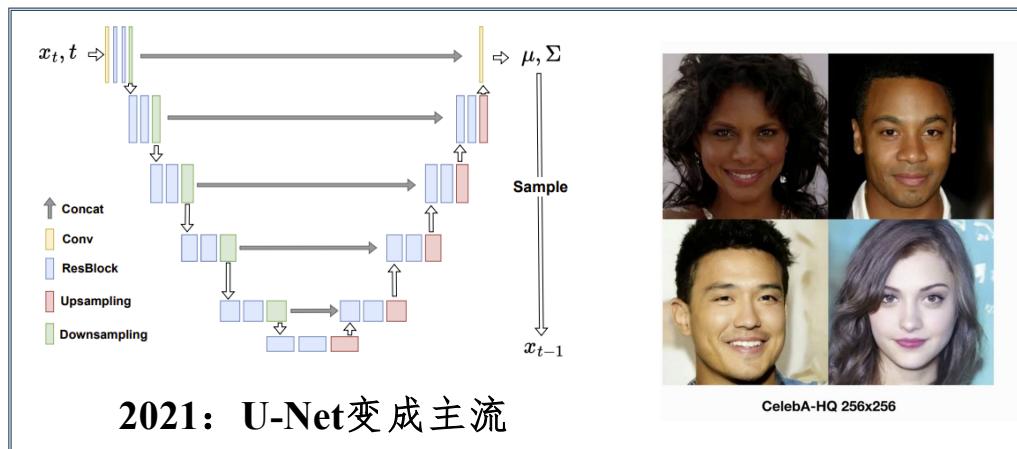
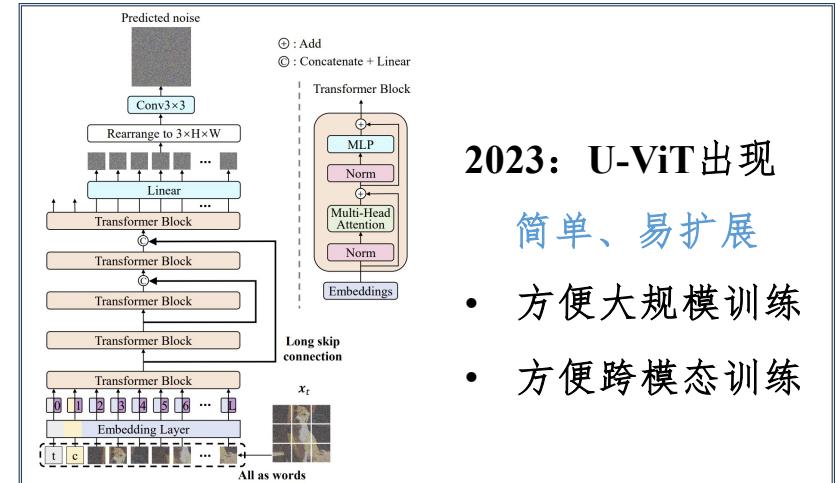
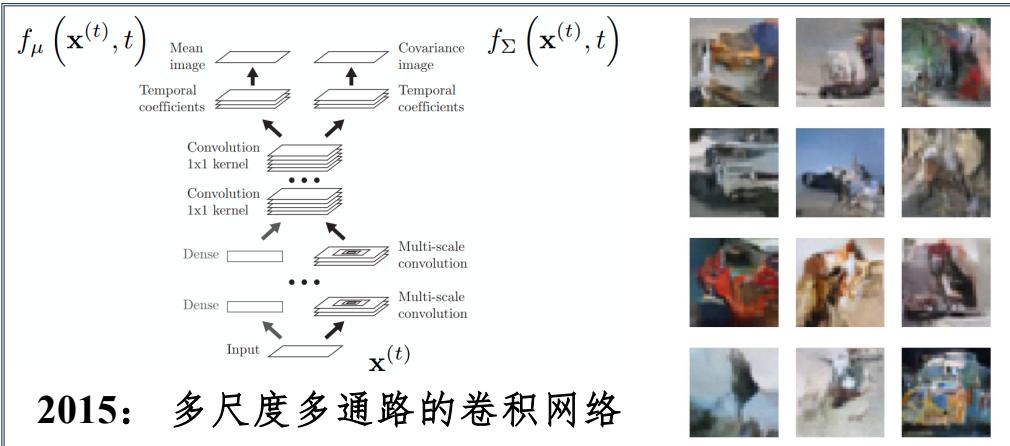
连续时间扩散模型：无限步数



- 对上述**SDE**、**ODE**进行离散化求解即可实现采样
- **SDE:**
 - **优点:** 持续的噪声注入可以帮助在扩散过程中弥补错误
 - **缺点:** 通常较慢，因为随机项在求解过程中需要细致的离散化
- **ODE:**
 - **优点:** 可以利用快速的ODE求解器，在需要非常快速的采样时效果最好
 - **缺点:** 没有“随机”错误校正，通常性能略低于随机采样



扩散模型的网络结构



MS-COCO 文到图领先的生成结果



扩散模型的优点总结

- 编码器 $q(z|x)$ 固定，不必学习
 - VAEs 需要同时学习 $q(z|x)$ 和 $p(x|z)$
- 训练目标足够简单
 - MSE loss: $\|\epsilon_\theta(x_t, t) - \epsilon\|^2$
- 收敛保证
 - 当总步数T足够多，反向过程的转移概率是高斯的
- 先进的网络结构
- 足够好的生成性能



扩散模型的方法研究：更可靠、普适、高效

- 基础改进（30min）
 - 对预训练分数预测模型的完善、校准、增强
 - 面向更高分辨率、多模态
 - ...
- 生成加速（30min）
 - 设计ODE Solver
 - 模型蒸馏、一致性模型
 - ...



一般扩散模型（如：**DDPM**）只学习逆向过程转移概率的高斯均值 $\mu_\theta(x_t, t)$ ，而方差采用手工设计，这是次优的



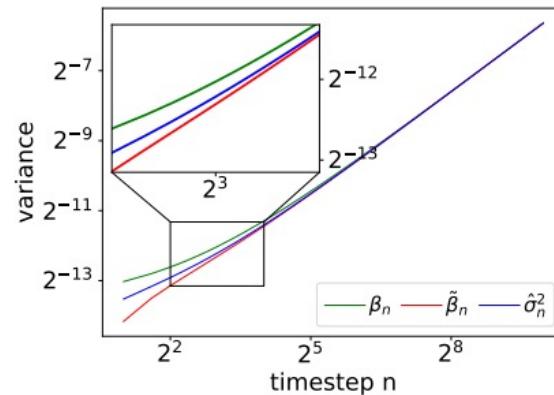
Analytic-DPM: 扩散模型的最优采样方差理论（隐变量模型视角出发）

- 证明最大似然意义下最优采样方差闭式解，改变了手工设计方差的范式

定理：扩散概率模型在最大似然意义
下关于评分函数/去噪函数的**最优采样
方差闭式解**如下：

$$\sigma_t^{*2} = \frac{\beta_t}{1-\beta_t} \left(1 - \beta_t \mathbb{E}_{q_t(x_t)} \frac{\|\nabla \log q_t(x_t)\|^2}{d} \right).$$

基于预训练模型和蒙特卡洛方法近似

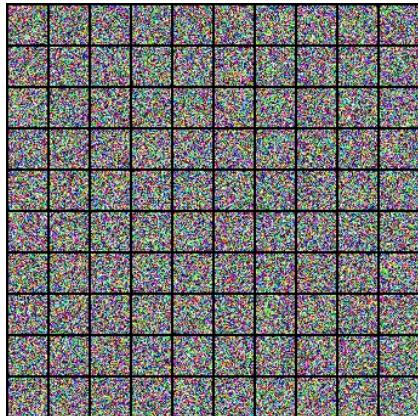


最优方差（蓝色）
与手工方差在零
时刻（即数据分
布）附近有显著
区别

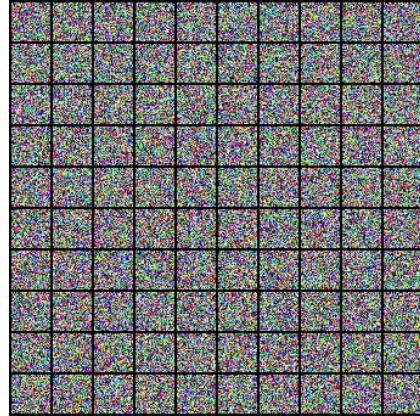


Analytic-DPM: 结果

- 无需额外训练，保证合成样本质量不变，相对DDPM至多加速 **20-80 倍**
- 作为核心技术部署于文到图生成大模型 **DALLE·2**



经典方法 **1000** 步



所提方法 **50** 步

To obtain a full generative model of images, we combine the CLIP image embedding *decoder* with a *prior* model, which generates possible CLIP image embeddings from a given text caption. We compare our text-to-image system with other systems such as DALL-E [40] and GLIDE [35], finding that our samples are comparable in quality to GLIDE, but with greater diversity in our generations. We also develop methods for training diffusion priors in latent space, and show that they achieve comparable performance to autoregressive priors, while being more compute-efficient. We refer to our full text-conditional image generation stack as *unCLIP*, since it generates images by inverting the CLIP image encoder.

For the AR prior, we use a Transformer text encoder with width 2048 and 24 blocks and a decoder with a causal attention mask, width 1664, and 24 blocks. For the diffusion prior, we use a Transformer with width 2048 and 24 blocks, and sample with Analytic DPM [2] with 64 strided sampling steps. To reuse hyperparameters tuned for diffusion noise schedules on images from [Dhariwal and Nichol [11]], we scale the CLIP embedding inputs by 17.2 to match the empirical variance of RGB pixel values of ImageNet images scaled to $[-1, 1]$.

	AR prior	Diffusion prior	64	64 → 256	256 → 1024
Diffusion steps	-	1000	1000	1000	1000
Noise schedule	-	cosine	cosine	cosine	linear
Sampling steps	-	64	250	27	15
Sampling variance method	-	analytic [2]	learned [34]	DDIM [47]	DDIM [47]
Crop fraction	-	-	0.25	0.25	0.25
Model size	1B	1B	3.5B	700M	300M
Channels	-	-	512	320	192
Depth	-	-	3	3	2
Channels multiple	-	-	1,2,3,4	1,2,3,4	1,1,2,2,4,4
Heads multiple	-	-	64	-	-
Attention resolution	-	-	32,16,8	-	-
Text encoder context	256	256	256	-	-
Text encoder width	2048	2048	2048	-	-
Text encoder depth	24	24	24	-	-
Text encoder heads	32	32	32	-	-

显著加速 **DALLE·2**



“a painting of a fox sitting in a field at sunrise in the style of Claude Monet”



在扩散模型的实际训练中，使用 $q_0(x_0)$ 采样的数据集近似损失函数 $\frac{1}{2} \int_0^T \omega(t) \mathbb{E}_{q_0(x_0)} \mathbb{E}_{q(\epsilon)} [\|\epsilon_\theta(x_t, t) - \epsilon\|_2^2] dt$ 中的期望，为训练模型引入偏差



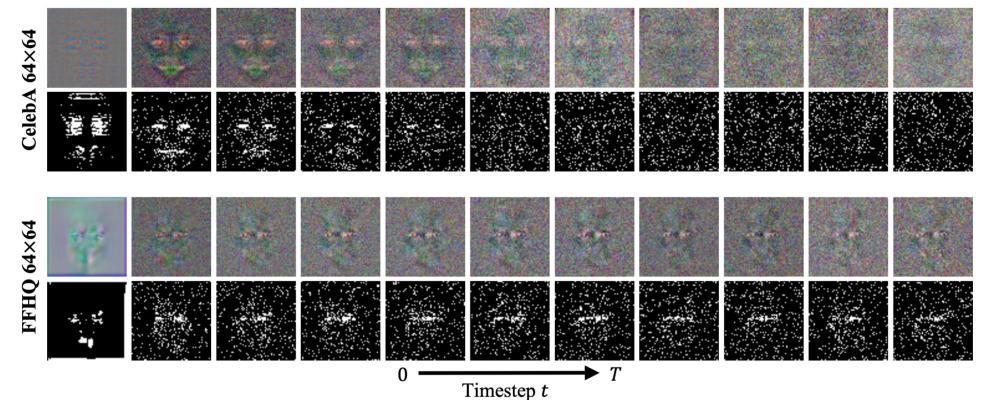
Calibrated-DPMs：扩散模型的校准（偏差消除）

观察：在温和的边界条件假设下，有

$$\mathbb{E}_{q_0(x_0)} \nabla_{x_0} \log q_0(x_0) = 0.$$

定理： $\alpha_t \nabla_{x_t} \log q_t(x_t)$ 的随机过程是关于 x_t 的逆时间过程的鞅，则

$$\mathbb{E}_{q_t(x_t)} \nabla_{x_t} \log q_t(x_t) = 0.$$



然而，实际训练的分数预测模型 **并非具有0均值**

- 将训练完的模型 $\epsilon_\theta(x_t, t)$ 校准为 $\epsilon_\theta(x_t, t) - \mathbb{E}_{q_t(x_t)} \epsilon_\theta(x_t, t)$ ，可降低模型的**score matching loss**，改善模型似然

基于蒙特卡洛方法或额外训练一个模型近似

Calibrated-DPMs：结果

- 无需额外训练，在多个数据集上提高合成样本质量，相对未校准模型提高 FID 至多 1.1

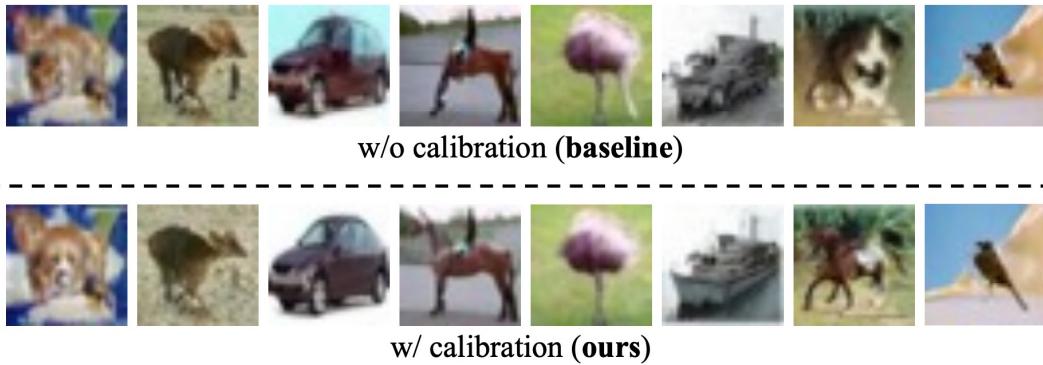


Table 1: Comparison on sample quality measured by $\text{FID} \downarrow$ with varying NFE on CIFAR-10. Experiments are conducted using a linear noise schedule on the discrete-time model from [15]. We consider three variants of DPM-Solver with different orders. The results with \dagger mean the actual NFE is order $\times \lfloor \frac{\text{NFE}}{\text{order}} \rfloor$ which is smaller than the given NFE, following the setting in [26].

Noise prediction	DPM-Solver	Number of evaluations (NFE)						
		10	15	20	25	30	35	40
$\epsilon_\theta^t(x_t)$	1-order	20.49	12.47	9.72	7.89	6.84	6.22	5.75
	2-order	7.35	$\dagger 4.52$	4.14	$\dagger 3.92$	3.74	$\dagger 3.71$	3.68
	3-order	$\dagger 23.96$	4.61	$\dagger 3.89$	$\dagger 3.73$	3.65	$\dagger 3.65$	$\dagger 3.60$
$\epsilon_\theta^t(x_t) - \mathbb{E}_{q_t(x_t)} [\epsilon_\theta^t(x_t)]$	1-order	19.31	11.77	8.86	7.35	6.28	5.76	5.36
	2-order	6.76	$\dagger 4.36$	4.03	$\dagger 3.66$	3.54	$\dagger 3.44$	3.48
	3-order	$\dagger 53.50$	4.22	$\dagger 3.32$	$\dagger 3.33$	3.35	$\dagger 3.32$	$\dagger 3.31$

Table 2: Comparison on sample quality measured by $\text{FID} \downarrow$ with varying NFE on CelebA 64×64 . Experiments are conducted using a linear noise schedule on the discrete-time model from [35]. The settings of DPM-Solver are the same as on CIFAR-10.

Noise prediction	DPM-Solver	Number of evaluations (NFE)						
		10	15	20	25	30	35	40
$\epsilon_\theta^t(x_t)$	1-order	16.74	11.85	7.93	6.67	5.90	5.38	5.01
	2-order	4.32	$\dagger 3.98$	2.94	$\dagger 2.88$	2.88	$\dagger 2.88$	2.84
	3-order	$\dagger 11.92$	3.91	$\dagger 2.84$	$\dagger 2.76$	2.82	$\dagger 2.81$	$\dagger 2.85$
$\epsilon_\theta^t(x_t) - \mathbb{E}_{q_t(x_t)} [\epsilon_\theta^t(x_t)]$	1-order	16.13	11.29	7.09	6.06	5.28	4.87	4.39
	2-order	4.42	$\dagger 3.94$	2.61	$\dagger 2.66$	2.54	$\dagger 2.52$	2.49
	3-order	$\dagger 35.47$	3.62	$\dagger 2.33$	$\dagger 2.43$	2.40	$\dagger 2.43$	$\dagger 2.49$



低质量的生成广泛存在，现有指标衡量分布的质量（如：IS、FID）或不能可靠反映出真实视觉质量（如：CLIPScore、ImageReward）
准确高效地检测出低质量生成，对提升用户体验非常重要



Stable Diffusion v1.5
ImageReward: 1.74



Stable Diffusion XL Base
ImageReward: 0.70

Preferred
by human



Stable Diffusion XL Base + Refiner
ImageReward: 0.75

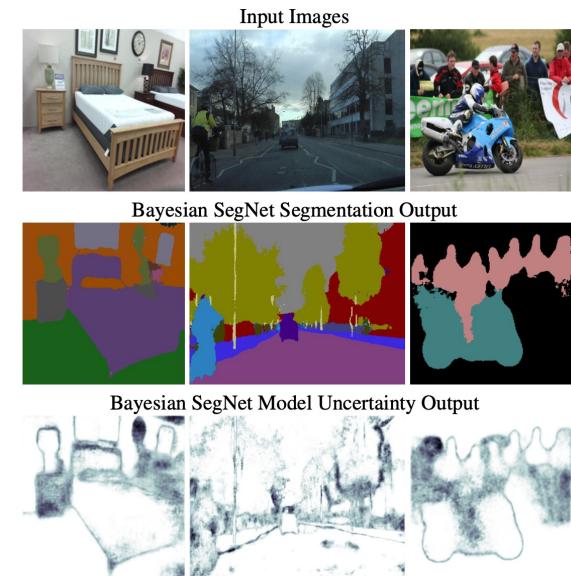
Prompt: A beautiful girl near the lake



低质量生成检测：从贝叶斯不确定性的视角

观察：

- 低质量的生成样本处于真实训练样本的流型之外，
是分布外样本
- 基于贝叶斯不确定性可以有效检测分布外样本
- 贝叶斯深度学习方法在传统图到图变换的应用中可
有效衡量不确定性

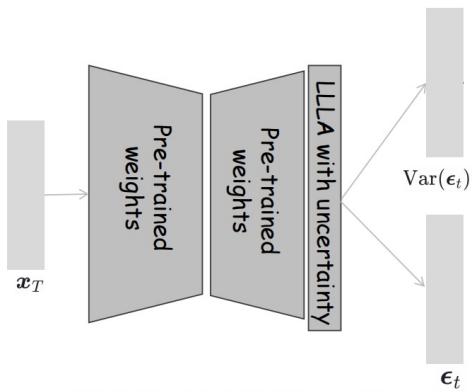


[Bayesian SegNet, Kendall et al.]

如何将贝叶斯深度学习技术融入扩散模型，实
现基于贝叶斯不确定性的低质量生成检测？



基于贝叶斯推断量化扩散模型生成样本的不确定性



- 基于最后层拉普拉斯近似方法，对预训练得分预测模型进行低成本处理，将原始的点预测转化为高斯分布预测

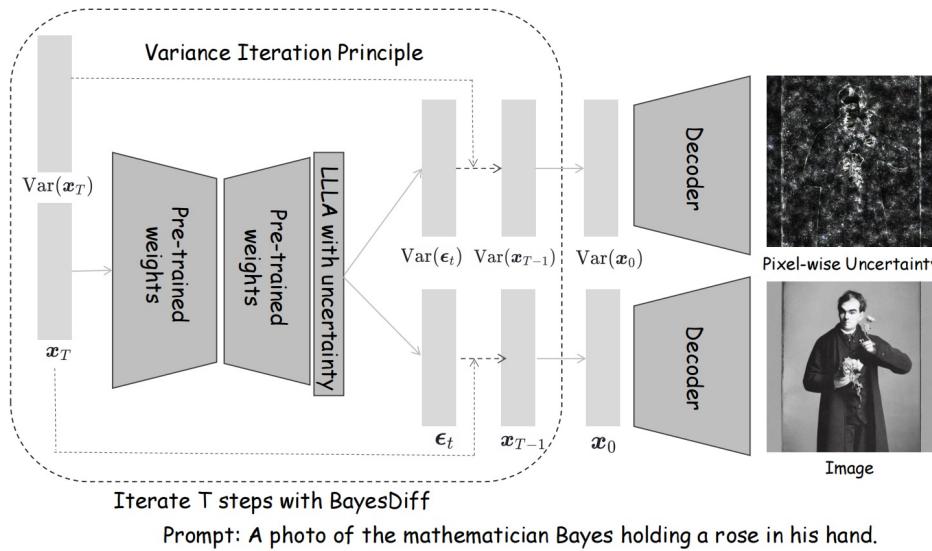
扩散模型的推理不是一蹴而就的，需要迭代得到最终预测（如：DDIM）：

$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha'_t}} (\mathbf{x}_t - \frac{1 - \alpha'_t}{\sqrt{1 - \bar{\alpha}'_t}} \epsilon_t) + \sqrt{\beta_t} \mathbf{z}$$

那么，如何量化最终生成内容的不确定性？



BayesDiff: 扩散模型中预测不确定性的动力学刻画



- 高斯设定下: 不确定性=方差

- 方差迭代:

$$\begin{aligned}\text{Var}(\mathbf{x}_{t-1}) &= \frac{1}{\alpha'_t} \text{Var}(\mathbf{x}_t) - 2 \frac{1 - \alpha'_t}{\alpha'_t \sqrt{1 - \bar{\alpha}'_t}} \text{Cov}(\mathbf{x}_t, \boldsymbol{\epsilon}_t) + \frac{(1 - \alpha'_t)^2}{\alpha'_t(1 - \bar{\alpha}'_t)} \text{Var}(\boldsymbol{\epsilon}_t) + \beta_t \\ \mathbb{E}(\mathbf{x}_{t-1}) &= \frac{1}{\sqrt{\alpha'_t}} \mathbb{E}(\mathbf{x}_t) - \frac{1 - \alpha'_t}{\sqrt{\alpha'_t(1 - \bar{\alpha}'_t)}} \mathbb{E}(\boldsymbol{\epsilon}_t)\end{aligned}$$

- 估计Cov项: 拆分 (全期望公式) +蒙特卡洛
- 跳跃机制 (只在部分推理步骤进行方差迭代)
 - 在引入不超过2x推理开销的条件下, 实现可靠的不确定性量化



BayesDiff：结果



Figure 3: The images with the highest (left) and lowest (right) uncertainty among 5000 unconditional generations of U-ViT model trained on ImageNet at 256×256 resolution.

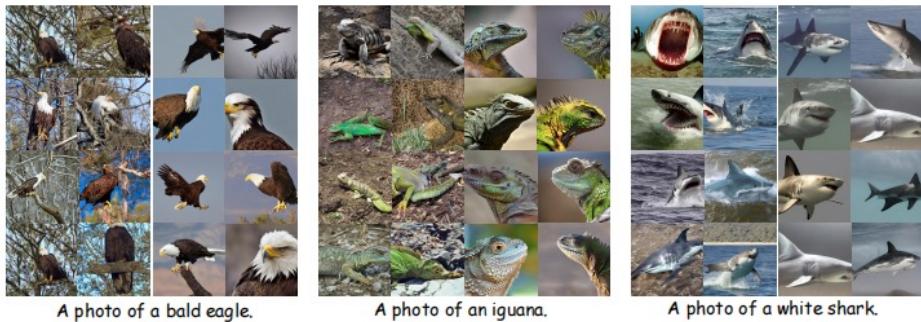


Figure 4: The images with the highest (left) and lowest (right) uncertainty among 80 generations on Stable Diffusion at 512×512 resolution.

像素上的不确定性相加得到图像不确定性，可有效检出低质量生成（如：**复杂背景、模糊、歧义**）

Table 1: Comparison on three metrics between randomly selected images and our selected images. We use 50 NFE for both DDIM and DPM-Solver sampler.

Model	Dataset	Sampler	FID ↓		Precision ↑		Recall ↑	
			random	ours	random	ours	random	ours
ADM	ImageNet 128	DDIM	8.65	8.48	0.661	0.665	0.655	0.653
ADM	ImageNet 128	2-order DPM-Solver	9.72	9.67	0.657	0.659	0.649	0.649
U-ViT	ImageNet 256	2-order DPM-Solver	7.21	6.81	0.698	0.705	0.658	0.657
U-ViT	ImageNet 512	2-order DPM-Solver	17.75	16.87	0.728	0.732	0.602	0.604

筛选后至多降低~0.9FID

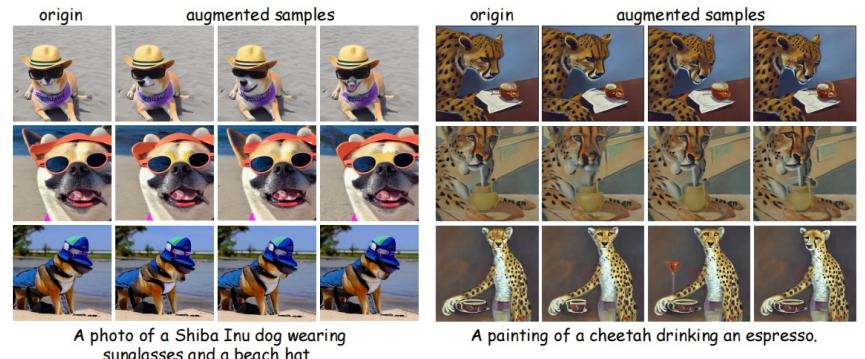


Figure 7: Examples of the augmentation of good generations with enhanced diversity on Stable Diffusion with DDIM sampler (50 NFE).

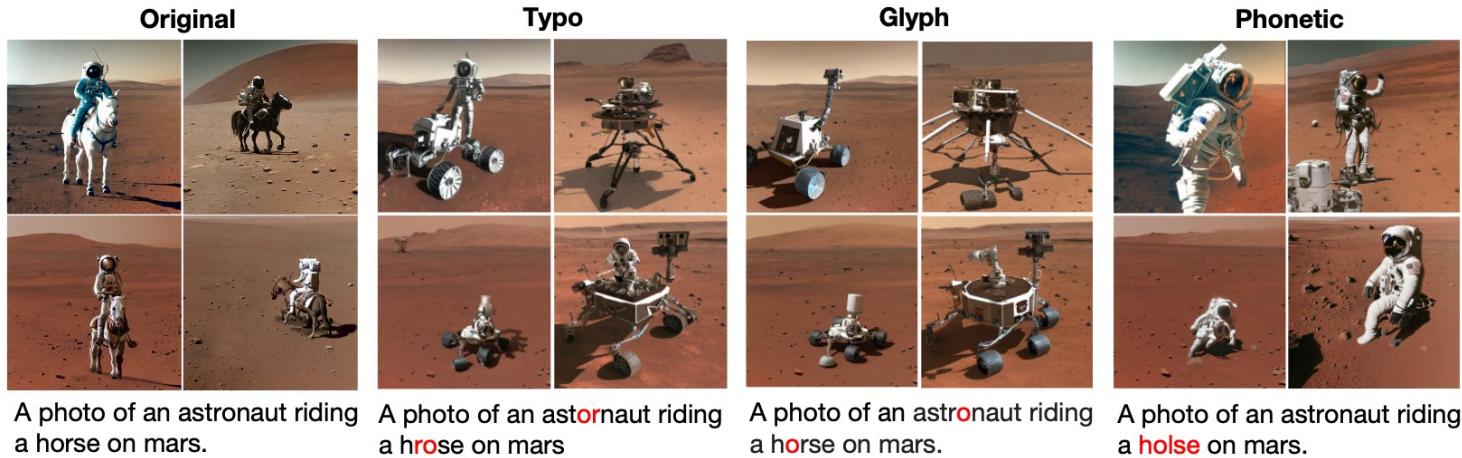
可以从中间的任意时刻隐状态的分布 $\mathcal{N}(\mathbb{E}(x_t), \text{Var}(x_t))$ 出发，进行重采样，实现**低成本数据增广**



扩散模型生成对输入提示的**敏感**程度，也
是影响用户体验的重要因素



文本-图像扩散模型的输入鲁棒性



Rule	Ori. Sentence	Adv. Sentence
Typo	A red ball on green grass under a blue sky.	A rde ball on green grass under a blue skky .
Glyph	A red ball on green grass under a blue sky.	A rd ball On green grass under a blue sky.
Phonetic	A red ball on green grass under a blue sky.	A read ball on green grass under a blue SKY .

基于typo、glyph、phonetic来模仿现实世界扰动



文本-图像扩散模型的输入鲁棒性

- 优化目标

- MMD距离:

$$D_{MMD}(p(x|c')\|p(x|c)) = \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N \kappa(x_i, x_j) - \frac{2}{N^2} \sum_{i=1}^N \sum_{j=1}^N \kappa(x_i, \bar{x}_j)$$

- KL:

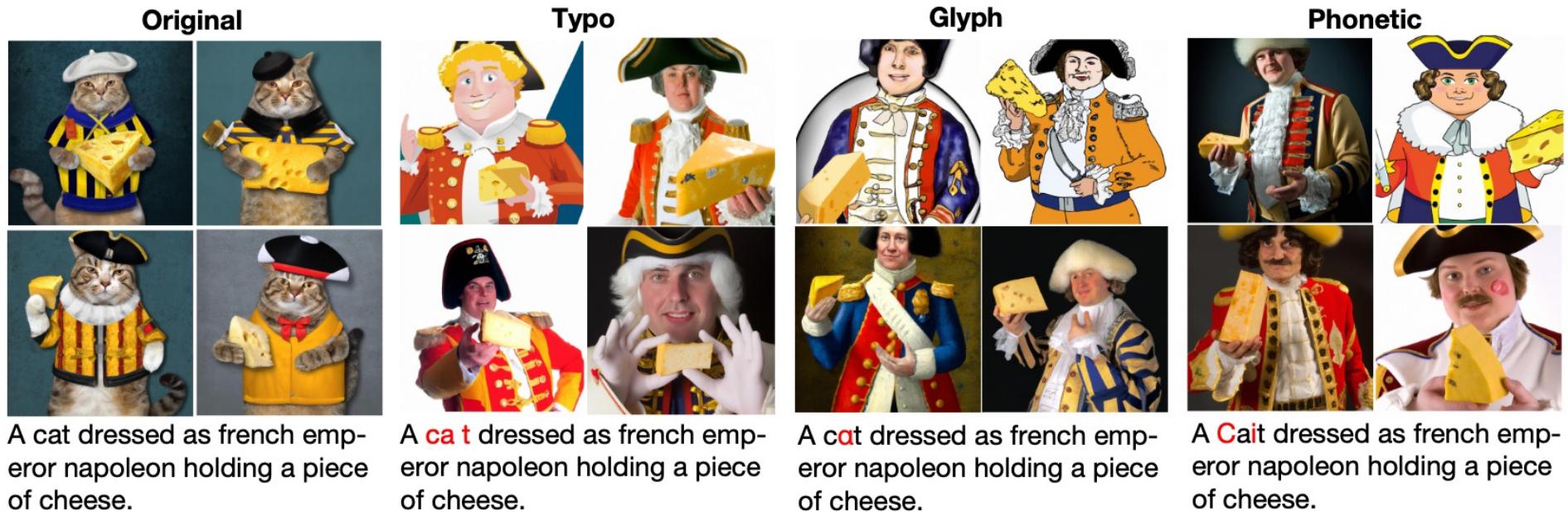
$$D_{KL}(p(x|c')\|p(x|c)) \approx \alpha \left[\frac{1}{N} \sum_1^N h_\phi(x_i) \right]^\top \left(g_\phi(c') - g_\phi(c) \right)$$

- 攻击方法

- 词重要性排序
 - 词级别扰动



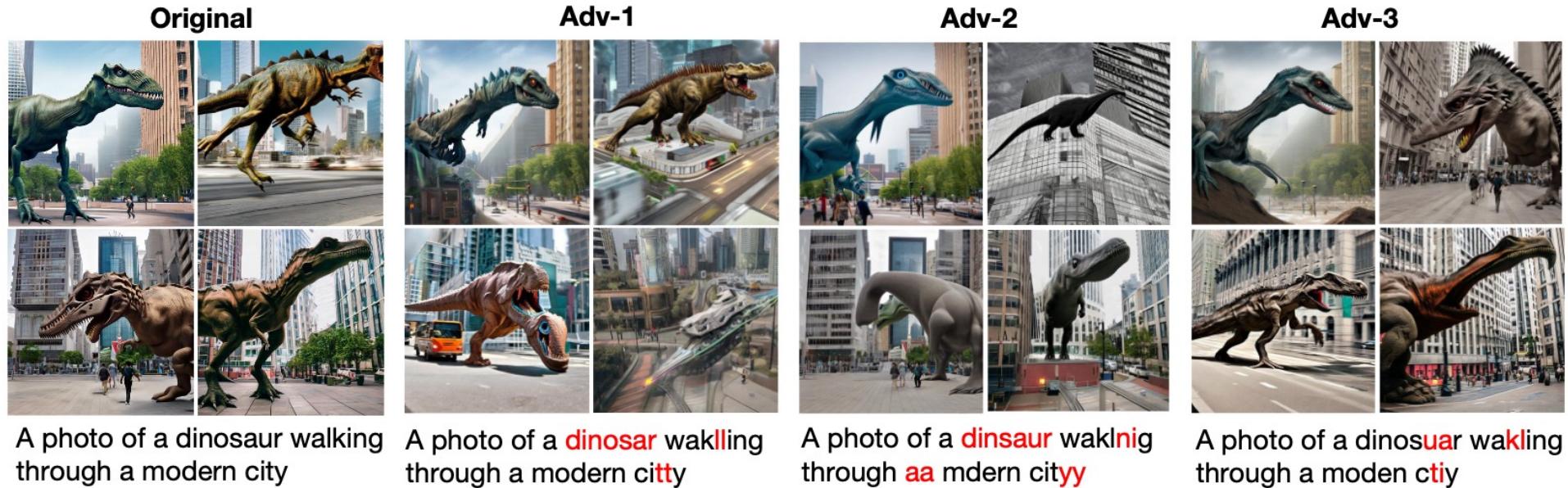
文本-图像扩散模型的输入鲁棒性：结果



Real-world attacks on DALLE-2.



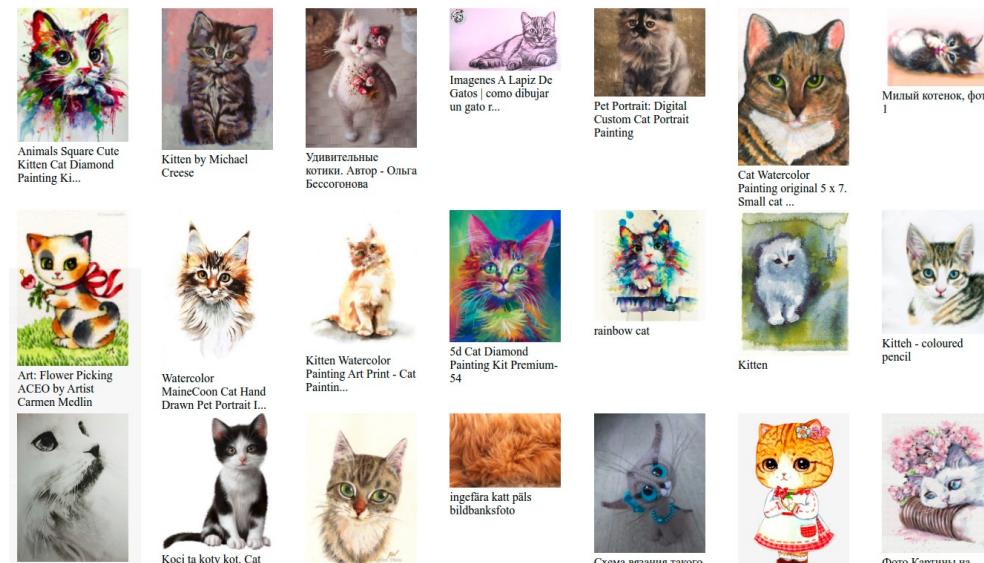
文本-图像扩散模型的输入鲁棒性：结果



Human (random) attacks on Stable Diffusion.



更高的分辨率和跨模态任务（如：文本到图像）
为扩散模型的模型构建和训练方法提出新的要求



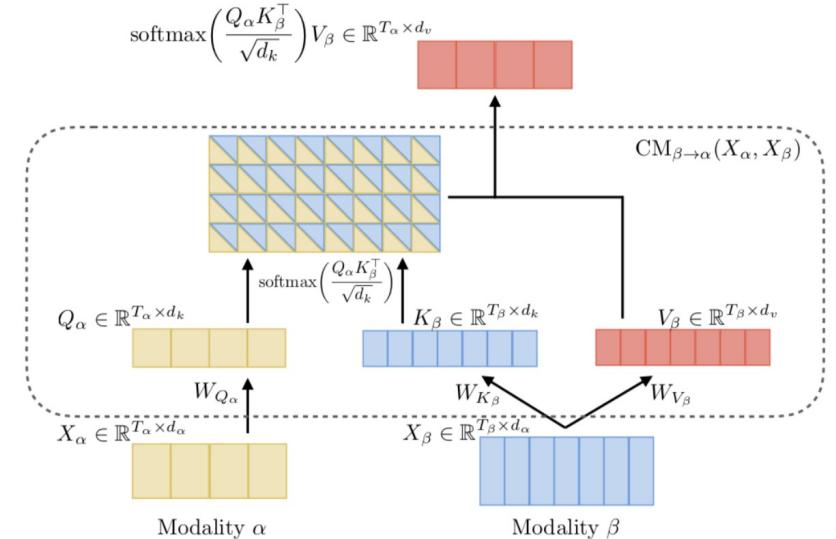
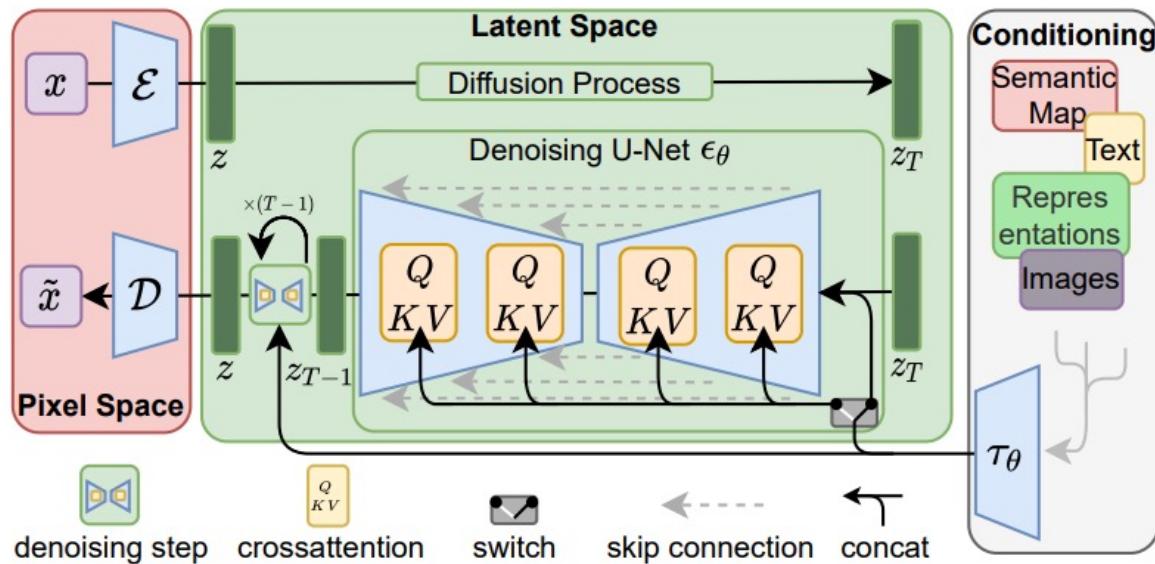
LAION: 开放域、高噪声、大规模



隐空间扩散模型

基于classifier-free guidance激发辅助信息：

$$\begin{aligned}\hat{\epsilon}_\theta(\mathbf{x}_t|y) &= s \cdot \epsilon_\theta(\mathbf{x}_t|y) + (1 - s) \cdot \epsilon_\theta(\mathbf{x}_t|0) \\ &= \epsilon_\theta(\mathbf{x}_t|0) + s \cdot (\epsilon_\theta(\mathbf{x}_t|y) - \epsilon_\theta(\mathbf{x}_t|0))\end{aligned}$$



隐空间条件模型

Cross Attention 模块

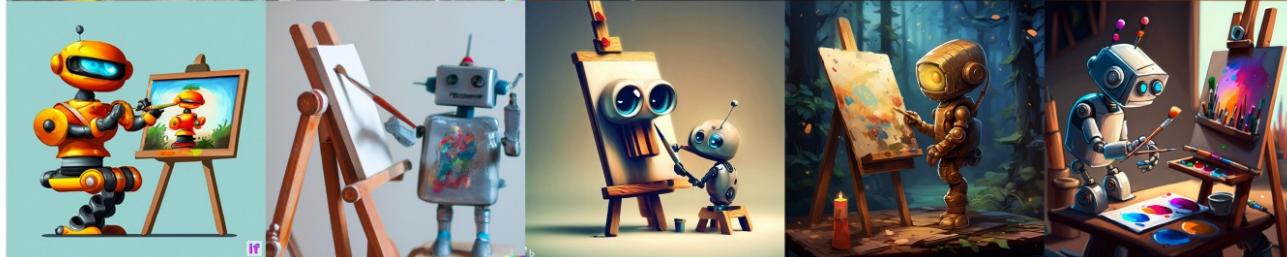


SDXL 生成结果

a cat drinking a pint of beer



a cute robot artist
painting on an easel
concept art



a green sign that says
"Very Deep Learning"
and is at the edge
of the Grand Canyon



DEEPMLOYD IF

DALLE-2

BING IMAGE CREATOR

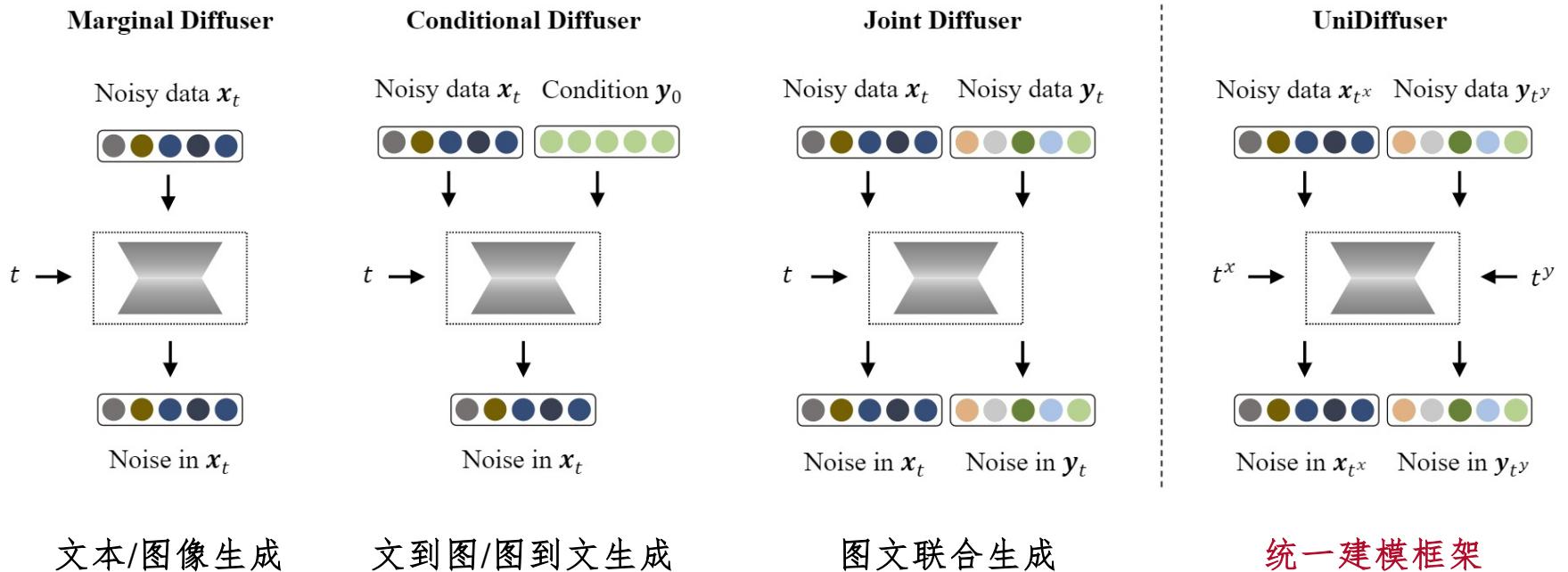
MIDJOURNEY v5.2

SDXL v0.9

大模型 + 大数据 + 适当算法/结构 = 强泛化、任务通用智能



多模态扩散概率模型：通用训练算法





Unidiffuer：文本-图像通用扩散概率大模型

- 文图通用模型
 - 适当增大模型
 - 训练时间不变
 - 推断时间不变
 - 推断效果可比
 - 处理 5 种任务

UniDiffuser

One Transformer Fits All Distributions in Multi-Modal Diffusion at Scale

- Joint Generation
- Unconditional Generation
- Text to Image Generation
- Image to Text Generation
- Image Variation
- Text Variation

清华大学
Tsinghua University

(a) $q(x_0|y_0)$ text & image joint generation

(b) $q(x_0|y_0)$ text to image generation

(c) $q(y_0|x_0)$ image to text generation

(d) $q(x_0)$ unconditional image generation

(e) $q(y_0)$ unconditional text generation

(f) $x_0 \xrightarrow{q(y_0|x_0)} y_0 \xrightarrow{q(x'_0|y_0)} x'_0$ image variation

(g) $y_0 \xrightarrow{q(x_0|y_0)} x_0 \xrightarrow{q(y'_0|x_0)} y'_0$ text variation

(h) $y_0 \xrightarrow{q(x_0|y_0)} x_0 \xrightarrow{q(y'_0|x_0)} y'_0 \xrightarrow{q(x'_0|y'_0)} x'_0 \xrightarrow{q(y''_0|x'_0)} y''_0 \xrightarrow{q(x''_0|y''_0)} x''_0 \dots \rightarrow$ Blocked Gibbs sampling between images and texts

(i) Interpolation between two images in the wild



模态上的新挑战I：开放域文本到三维内容生成

A blue jay standing on a large basket of rainbow macarons

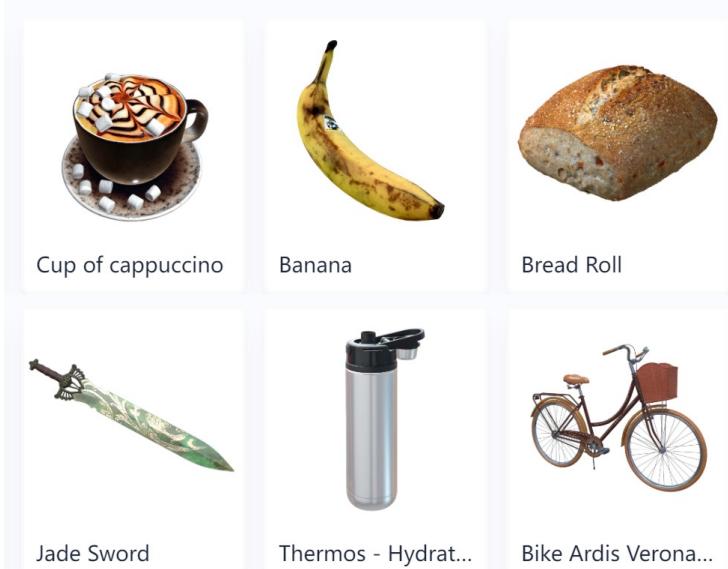
一只冠蓝鸦站在一大篮彩虹马卡龙上





挑战：数据量小

Objaverse: 特定域、低噪声、小规模 (**800K**)



Cup of cappuccino

Banana

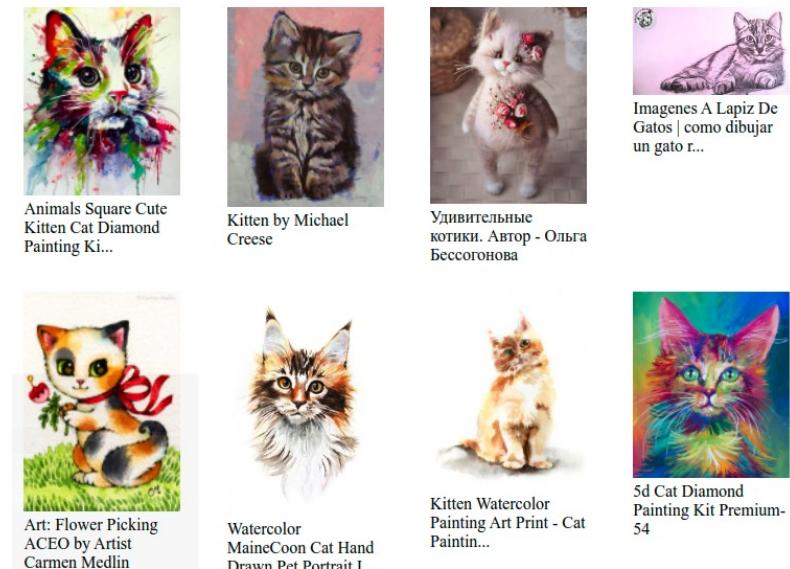
Bread Roll

Jade Sword

Thermos - Hydrat...

Bike Ardis Verona...

LAION: 开放域、高噪声、大规模 (**5B, 400M**)



Animals Square Cute Kitten Cat Diamond Painting Ki...

Kitten by Michael Creese

Удивительные котики. Автор - Ольга Бессогонова

Art: Flower Picking ACEO by Artist Carmen Medlin

Watercolor MaineCoon Cat Hand Drawn Pet Portrait I...

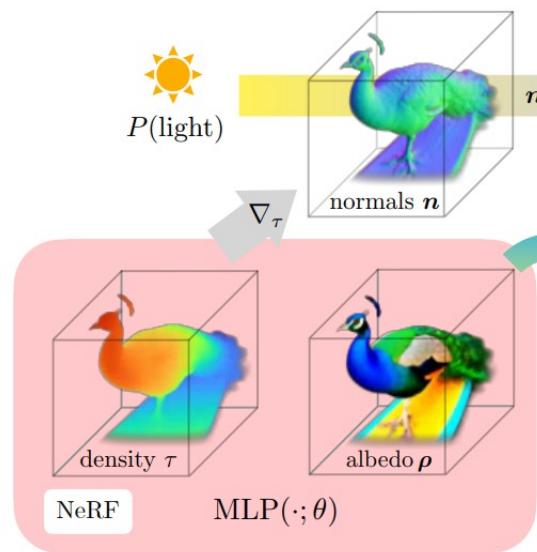
5d Cat Diamond Painting Kit Premium-54

如何在样本量不充分的情况下泛化到开放域文本？

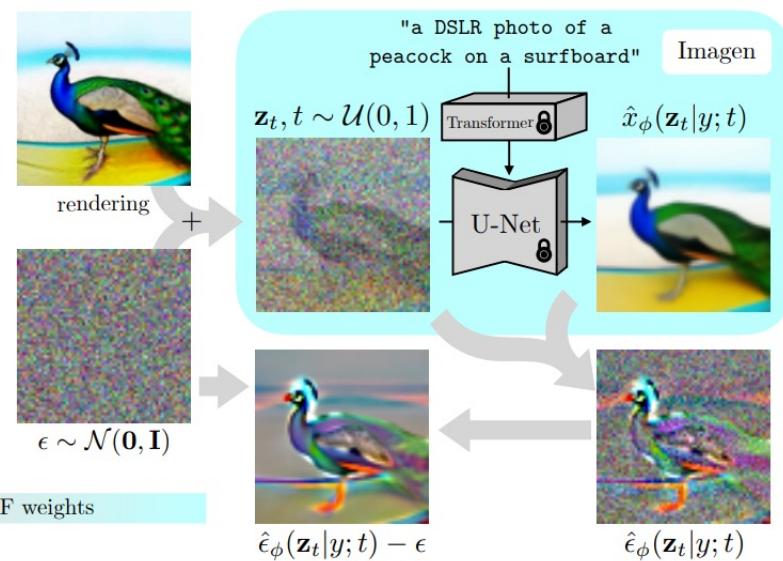


DreamFusion: 将图像模型蒸馏为3D模型

三维结构表示与可微渲染过程



基础扩散模型定义的图像先验分布



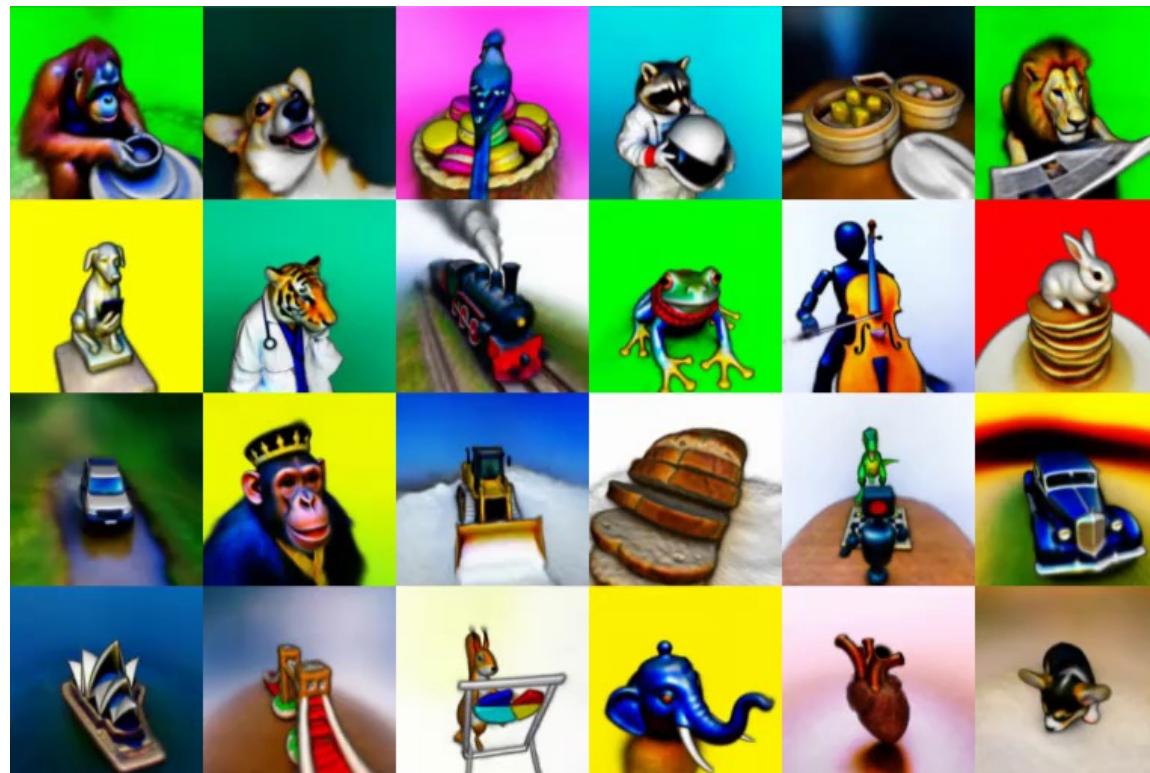
优化三维表示使各个视角渲染图片 “符合” 先验分布，无需3D数据

Score distillation sampling (SDS) 目标：渲染图片加入噪声，基础二维扩散模型能准确预测噪声

$$\nabla_{\theta} \mathcal{L}_{\text{SDS}}(\theta) := \mathbb{E}_{t, \epsilon, c} \left[\omega(t) (\epsilon_{\text{pretrain}}(\mathbf{x}_t, t, y) - \epsilon) \frac{\partial g(\theta, c)}{\partial \theta} \right]$$



DreamFusion：零样本文到三维数据合成结果





DreamFusion 系列工作

- 系列工作尝试提升三维结构表示和基础模型部分，算法均为 SDS
- 蒸馏算法是瓶颈：过饱和、过曝、多样性低等现象严重！



DreamFusion



Magic3D



SJC



Latent-NeRF



Fantasia3D



Score distillation sampling

- 寻找概率分布的极大值点，而非采样！

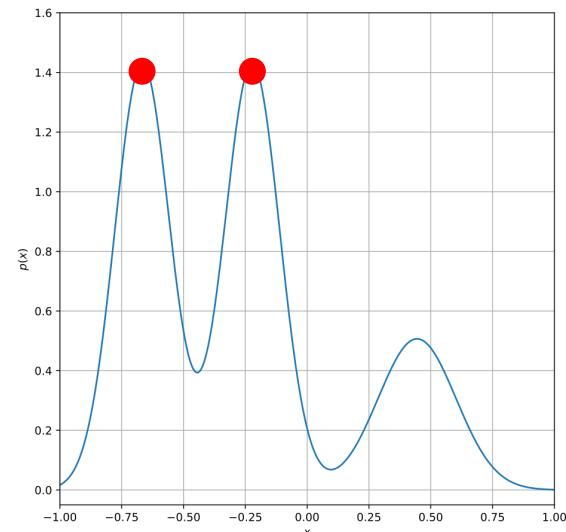
$$\min_{\theta \in \Theta} \mathcal{L}_{\text{SDS}}(\theta) := \mathbb{E}_{t,c} \left[(\sigma_t/\alpha_t) \omega(t) D_{\text{KL}}(q_t^\theta(\mathbf{x}_t|c) \parallel p_t(\mathbf{x}_t|y^c)) \right]$$

$$\nabla_\theta \mathcal{L}_{\text{SDS}}(\theta) \triangleq \mathbb{E}_{t,\epsilon,c} \left[\omega(t) (\epsilon_{\text{pretrain}}(\mathbf{x}_t, t, y) - \epsilon) \frac{\partial \mathbf{g}(\theta, c)}{\partial \theta} \right]$$

score function zero-mean

$$\approx \mathbb{E}_{t,\epsilon,c} \left[-\omega(t) \sigma_t \nabla_{\mathbf{x}_t} \log p_t(\mathbf{x}_t, y) \frac{\partial \mathbf{g}(\theta, c)}{\partial \theta} \right]$$

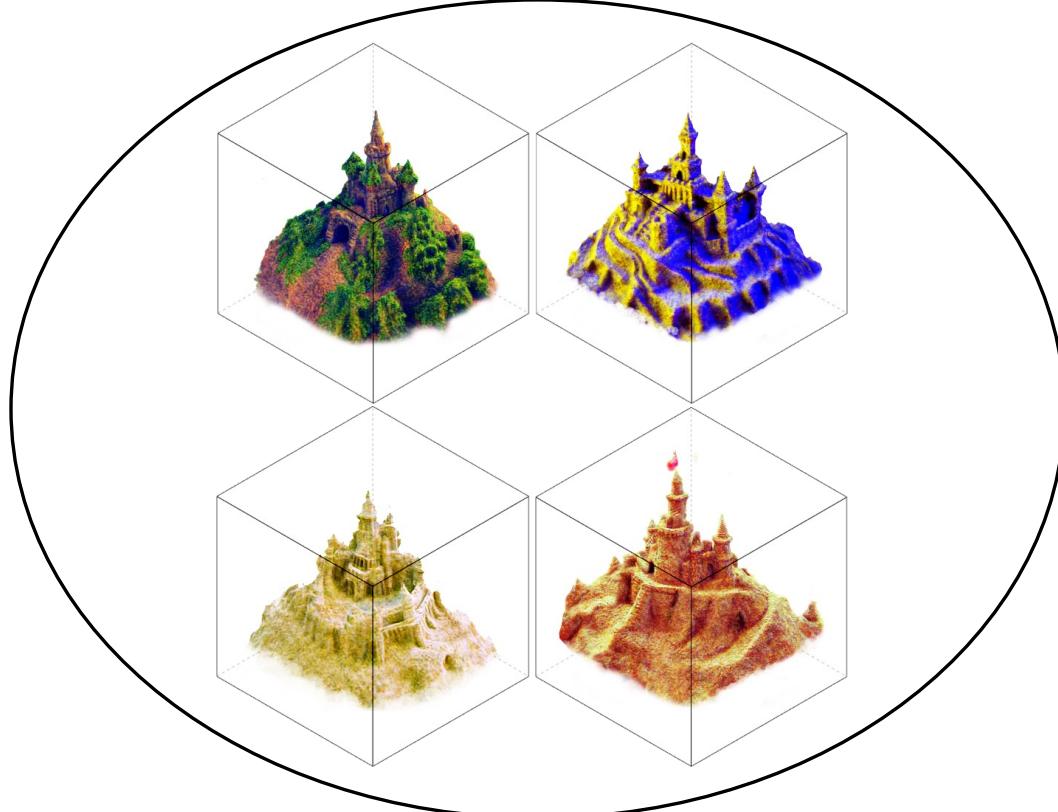
mode-seeking
in 2D space



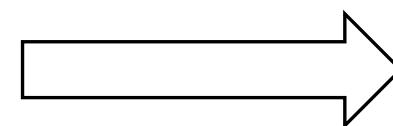


ProlificDreamer: 刻画文本到三维内容生成的不确定性

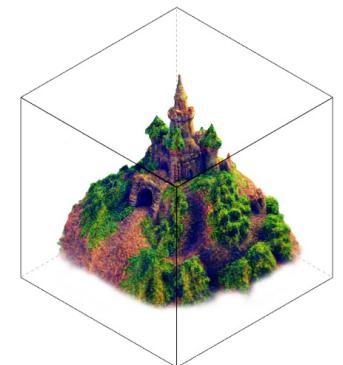
给定文本，隐式定义了 3D 模型的分布



从中采样（而非取极值）

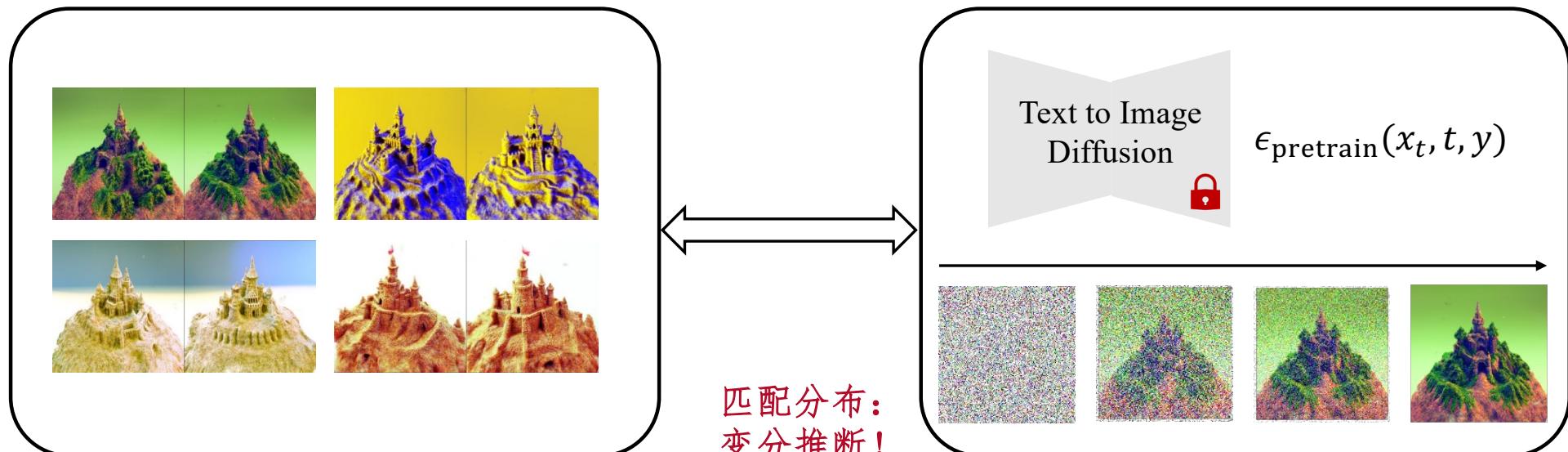


目的：提高保真度和多样性





文到3D生成：变分推断视角



三维内容分布诱导的渲染图像分布

基础扩散模型定义的图像分布

$$\min KL(\text{渲染图像分布} \parallel \text{二维模型分布})$$



Variational score distillation (VSD) 算法

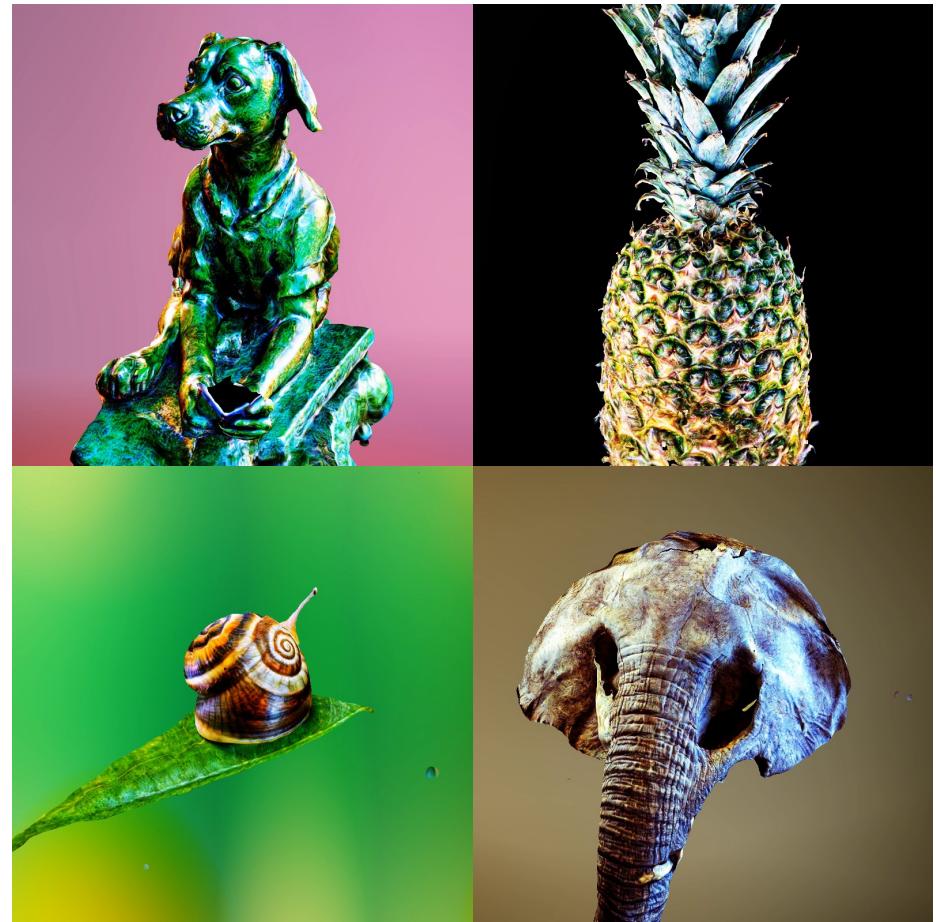
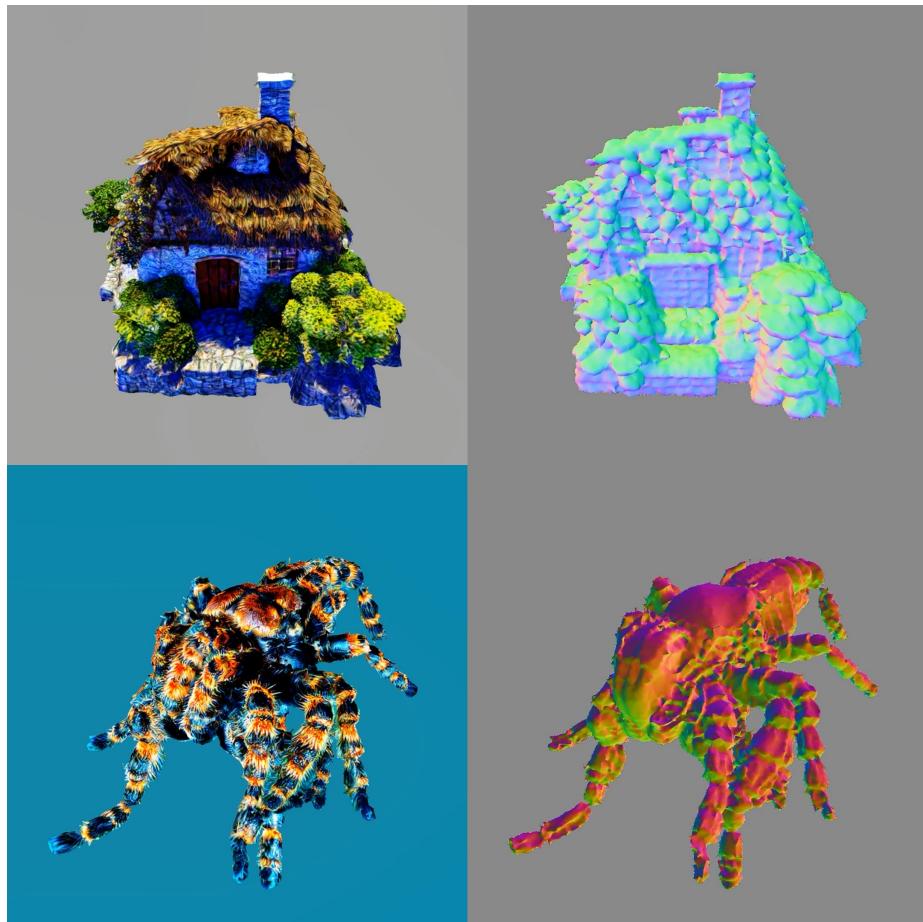
- 基于粒子的变分推断保证粒子优化后 i.i.d. 二维模型分布

定理：Wasserstein gradient flow of VSD.

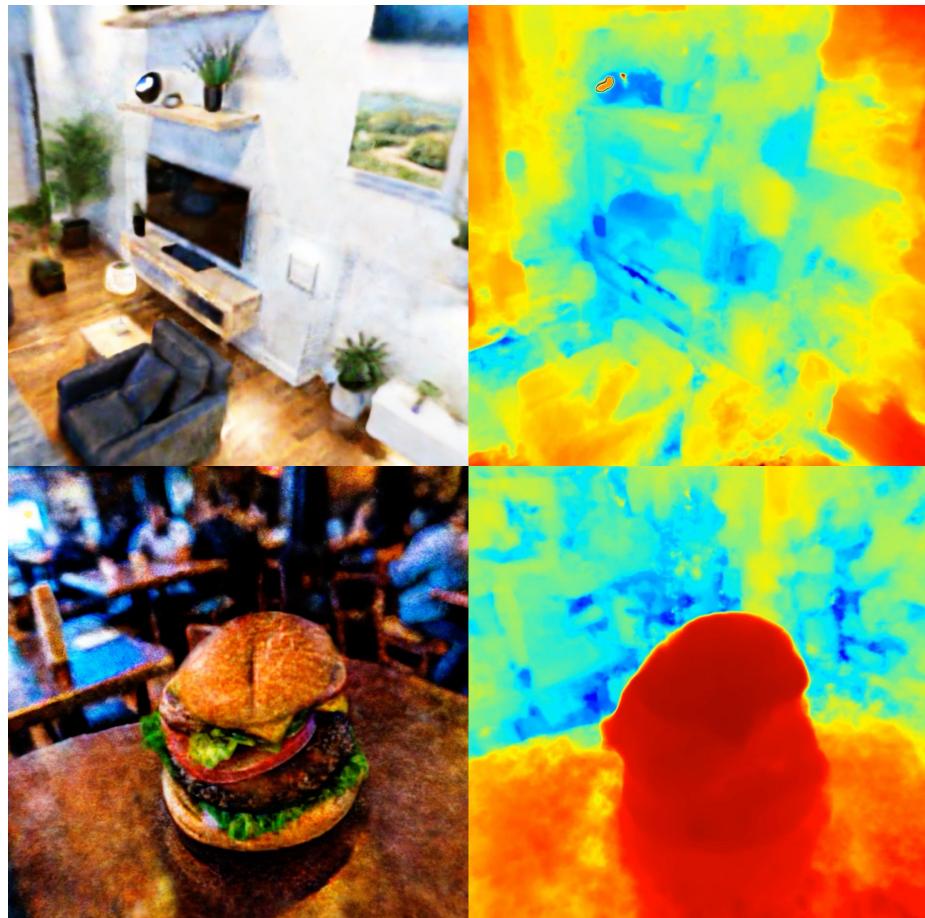
$$\frac{d\theta_\tau}{d\tau} = -\mathbb{E}_{t,\epsilon,c} \left[\omega(t) \left(\underbrace{-\sigma_t \nabla_{\mathbf{x}_t} \log p_t(\mathbf{x}_t | y^c)}_{\text{score of noisy real images}} - \underbrace{(-\sigma_t \nabla_{\mathbf{x}_t} \log q_t^{\mu_\tau}(\mathbf{x}_t | c, y))}_{\text{score of noisy rendered images}} \right) \frac{\partial \mathbf{g}(\theta_\tau, c)}{\partial \theta_\tau} \right]$$

已知二维模型分布 未知渲染图像分布，采用 **LoRA** 估计
VSD 中对应项为已知高斯噪声

Mesh: 高保真度、几何细节丰富

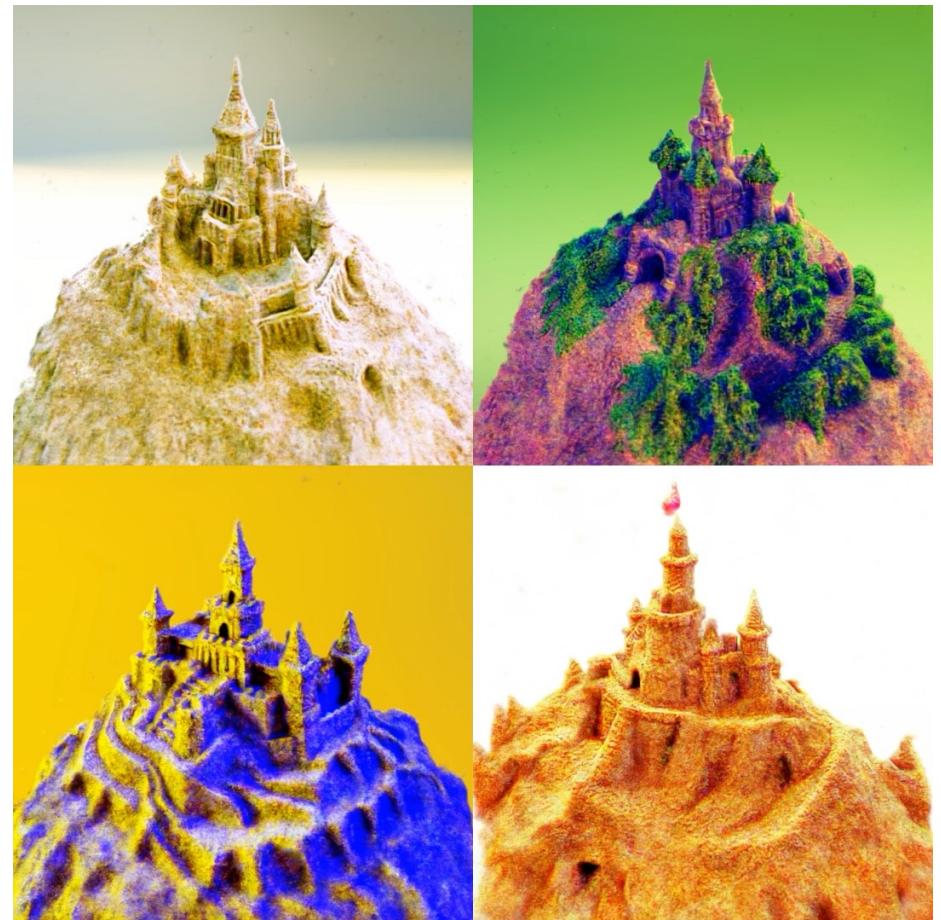


NeRF：高渲染精度、场景、半透明效果

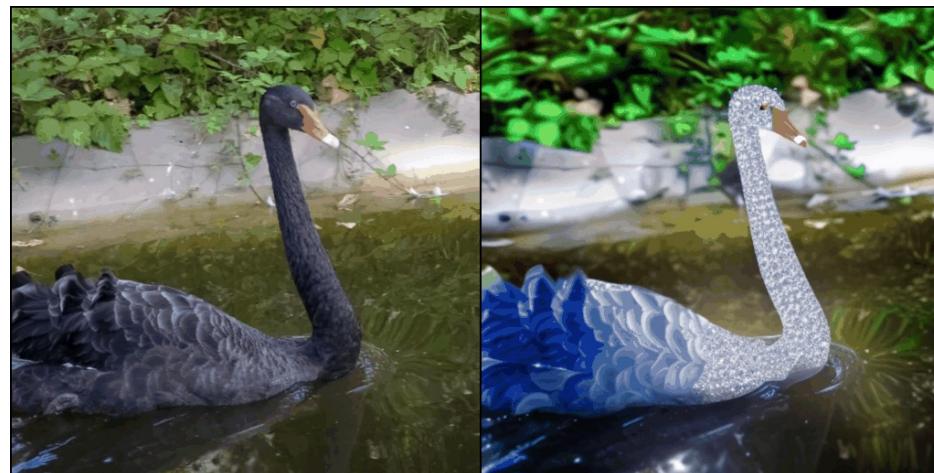




同一个文本的多样性



模态上的新挑战II：可控视频编辑

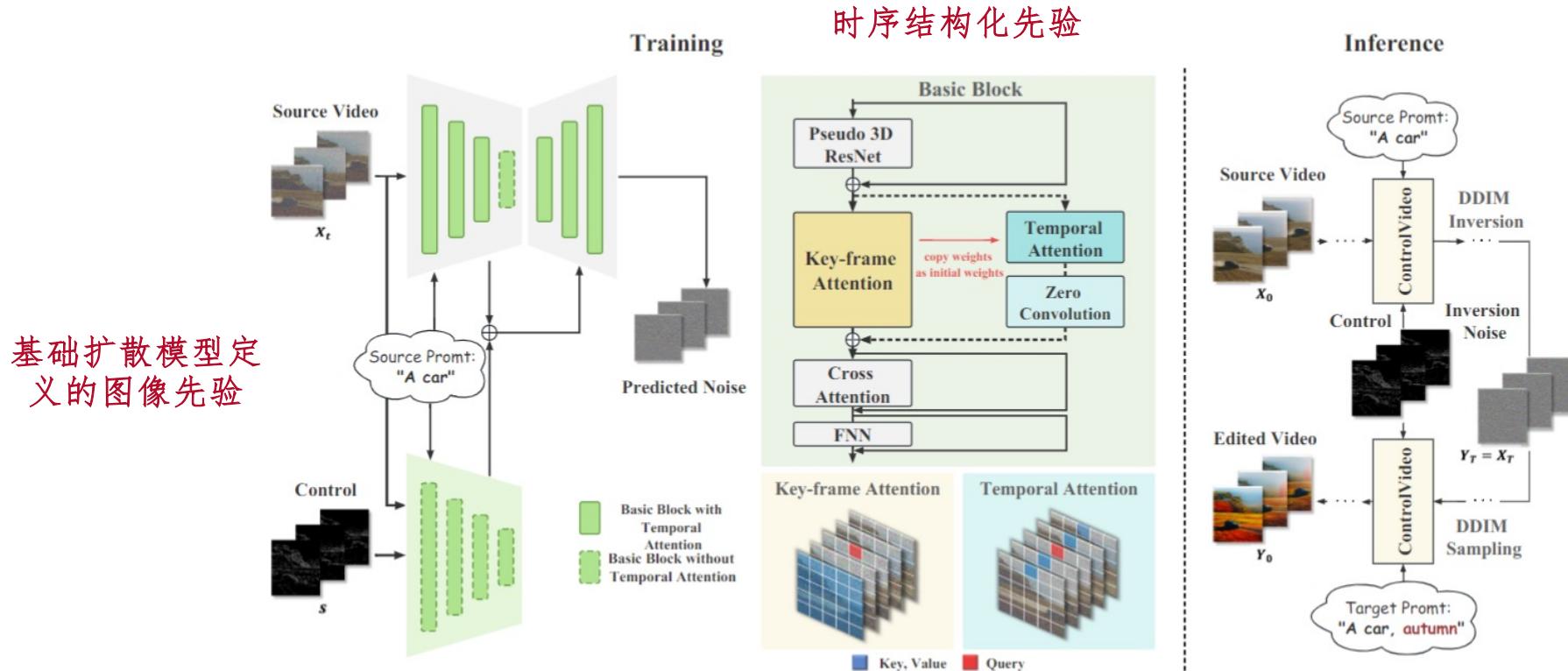


核心：时间一致性

swan→ Swarovski crystal swan



ControlVideo：单样本视频-文本数据做细粒度可控视频编辑



逐帧加入控制条件，加入关键帧和时序注意力机制，精心初始化，单视频微调



ControlVideo：结果

Source

ControlVideo

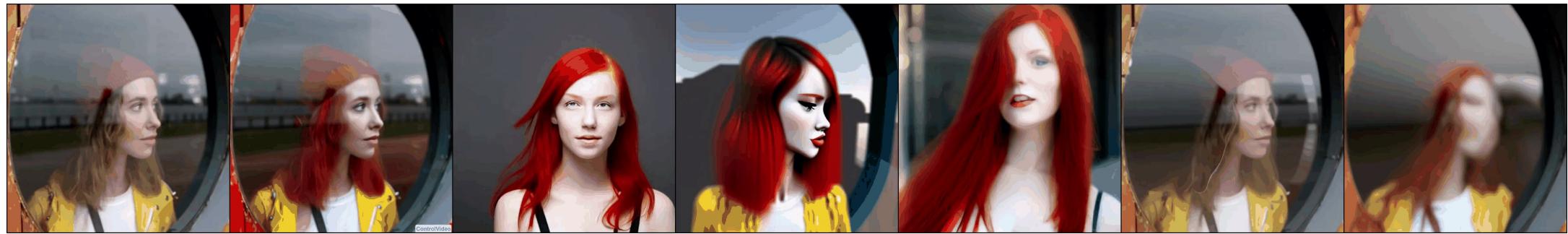
SD

Tune-A-Video

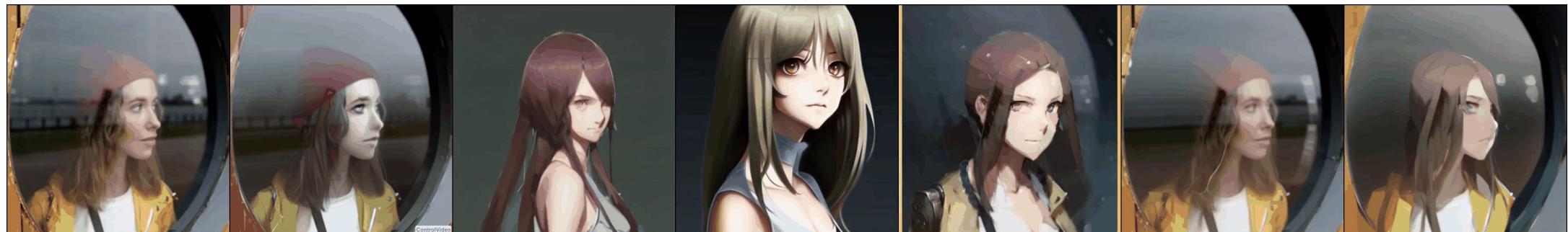
Vid2vid-zero

Video-P2P

FateZero



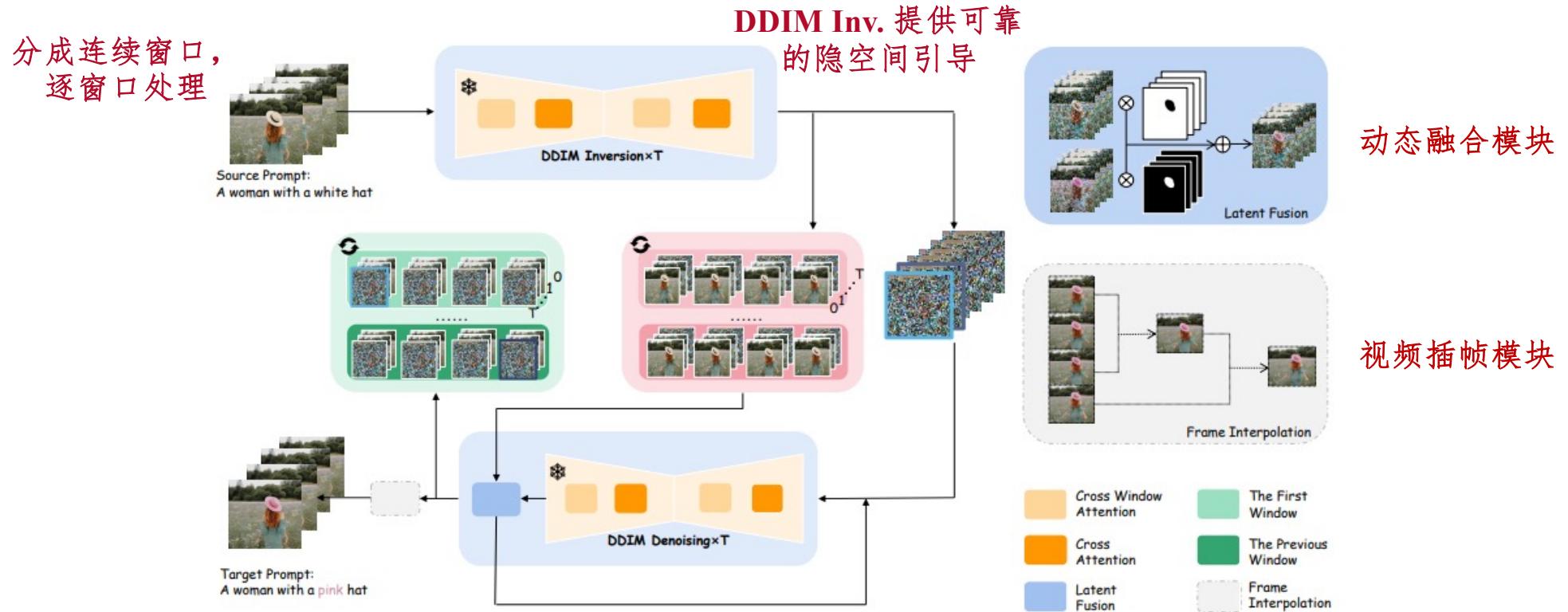
+ with red hair



+ Krenz Cushart style

权衡可编辑性、逼真程度、时间一致性、原始内容

LOVECon: 基于ControlNet、无需训练、更长视频编辑

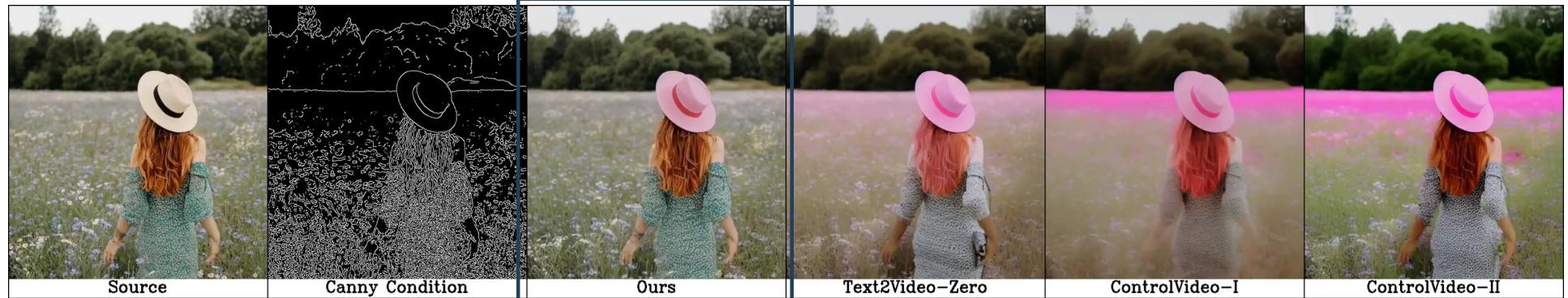


将自注意力改造为跨窗口注意力保证连贯生成，将原视频的DDIM Inv.状态与生成状态进行动态融合保证无关信息一致，引入视频插帧模型进行后处理提高时序平滑性



LOVECon : 结果

A woman with a white hat -> A woman with a pink hat



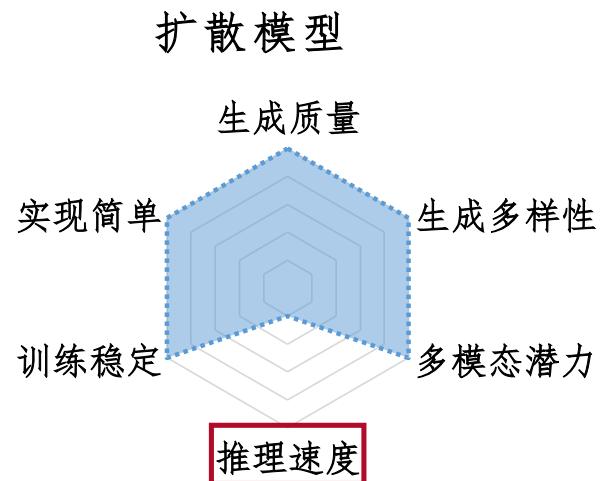
Flamingos -> Flamingos in the blue water



生成的更长、更连贯，与原始内容尽可能一致

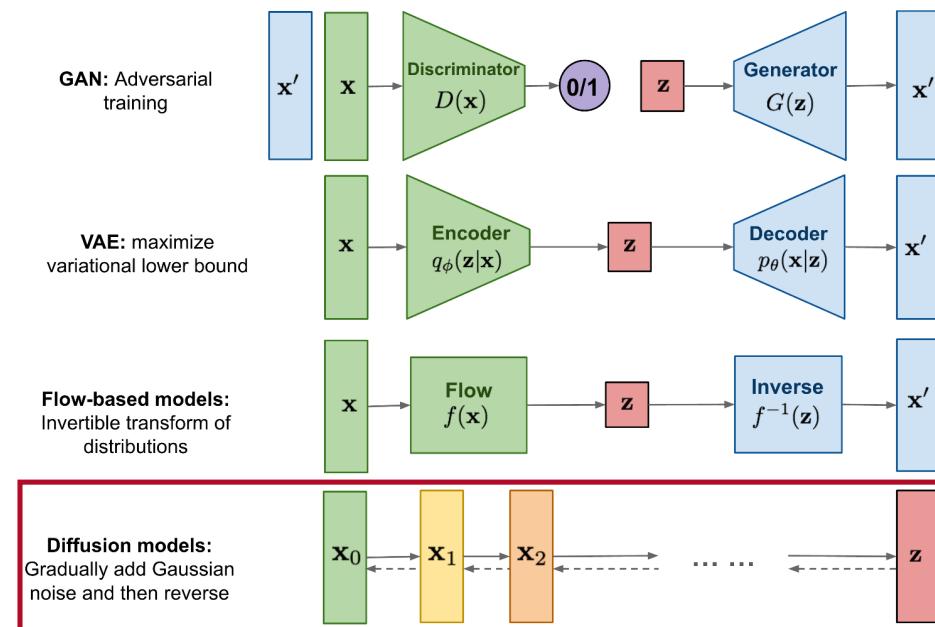


采样效率是扩散模型的**瓶颈问题**





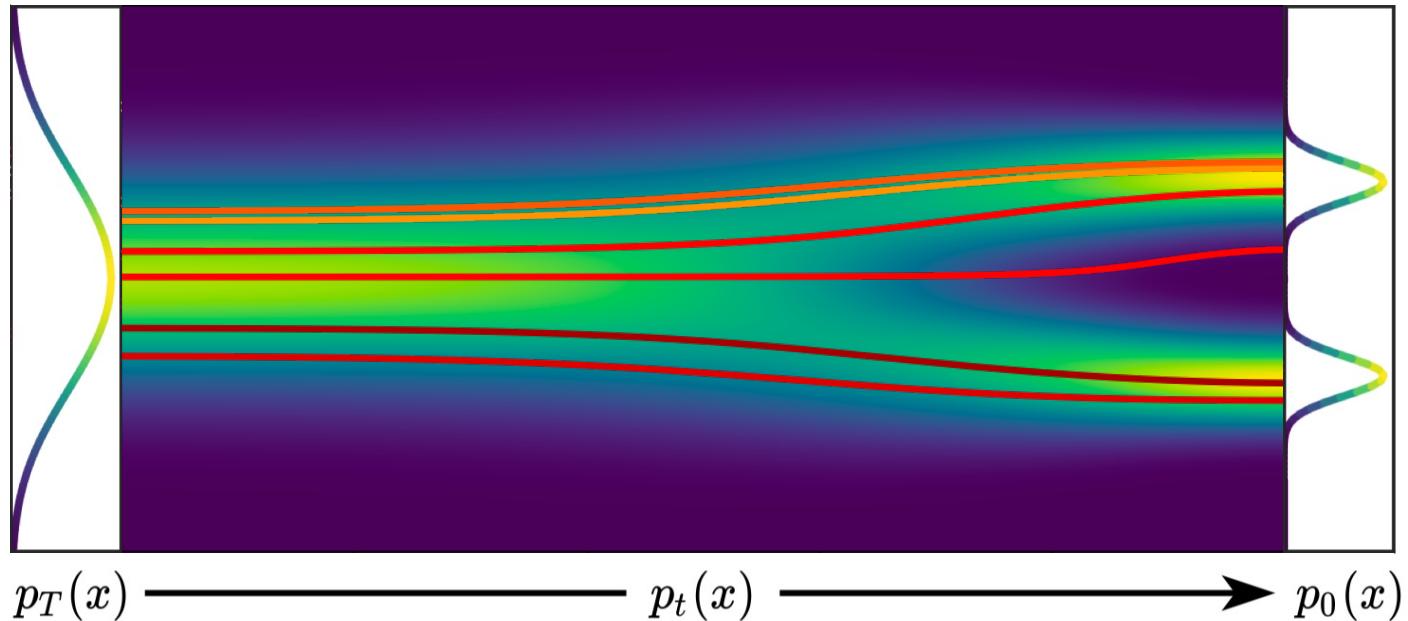
采样效率低：每个去噪步都需要一次模型前传



原则上需要迭代1000次，每次需调用神经网络



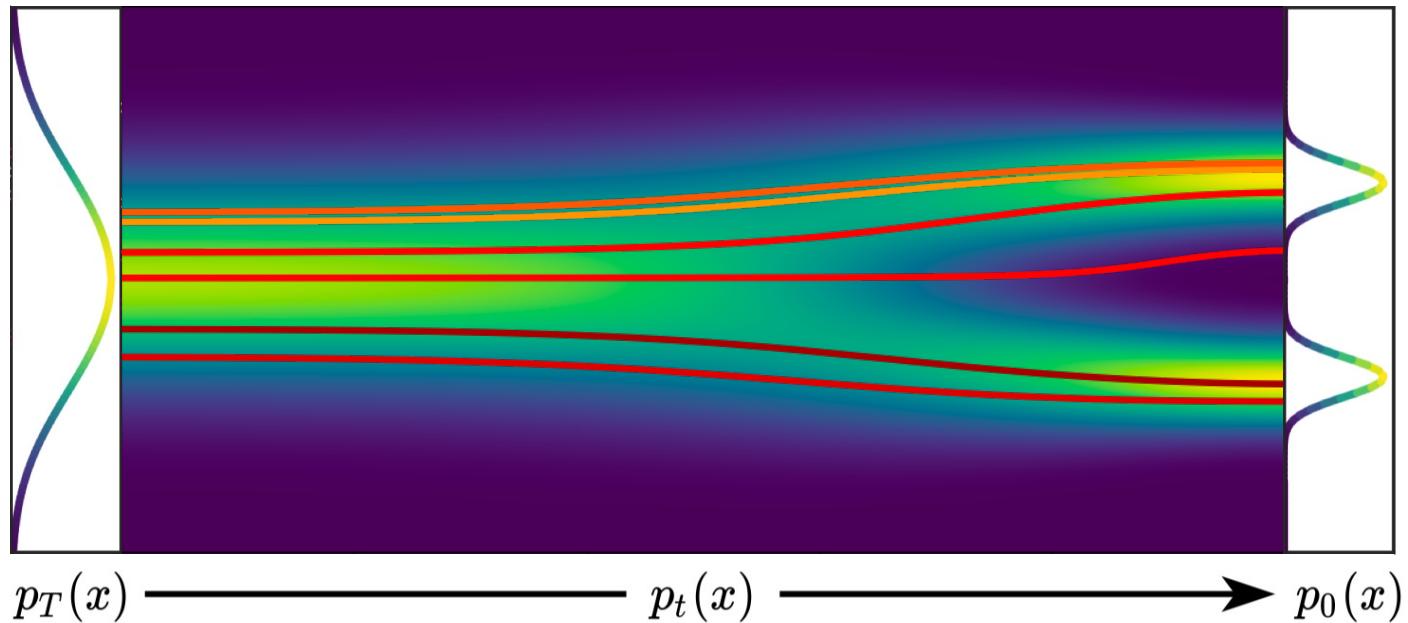
出发点：常微分方程的视角



时时刻刻边缘分布相同，但是路径上没有噪声！



扩散模型采样等价常微分方程离散化



Sampling method	Steps to converge
Traditional SDE Solvers	~200
Traditional ODE Solvers	~100

Checkpoint: CIFAR-10, VP
[Song et al., ICLR'21]



DPM-Solver: 面向扩散概率模型的常微分方程离散化

- 针对扩散概率模型半线性等特点，设计等价常微分方程的离散化解析形式

经典龙格库塔法

$$\mathbf{x}_t = \mathbf{x}_s + \int_s^t \left(f(\tau) \mathbf{x}_\tau + \frac{g^2(\tau)}{2\sigma_\tau} \epsilon_\theta(\mathbf{x}_\tau, \tau) \right) d\tau$$

整体黑盒泰勒展开并做差分近似

所提 DPM-Solver

$$\mathbf{x}_{t_{i-1} \rightarrow t_i} = \frac{\alpha_{t_i}}{\alpha_{t_{i-1}}} \tilde{\mathbf{x}}_{t_{i-1}} - \alpha_{t_i} \sum_{n=0}^{k-1} \hat{\epsilon}_\theta^{(n)}(\hat{\mathbf{x}}_{\lambda_{t_{i-1}}}, \lambda_{t_{i-1}}) \int_{\lambda_{t_{i-1}}}^{\lambda_{t_i}} e^{-\lambda} \frac{(\lambda - \lambda_{t_{i-1}})^n}{n!} d\lambda + \mathcal{O}(h_i^{k+1})$$

解析形式

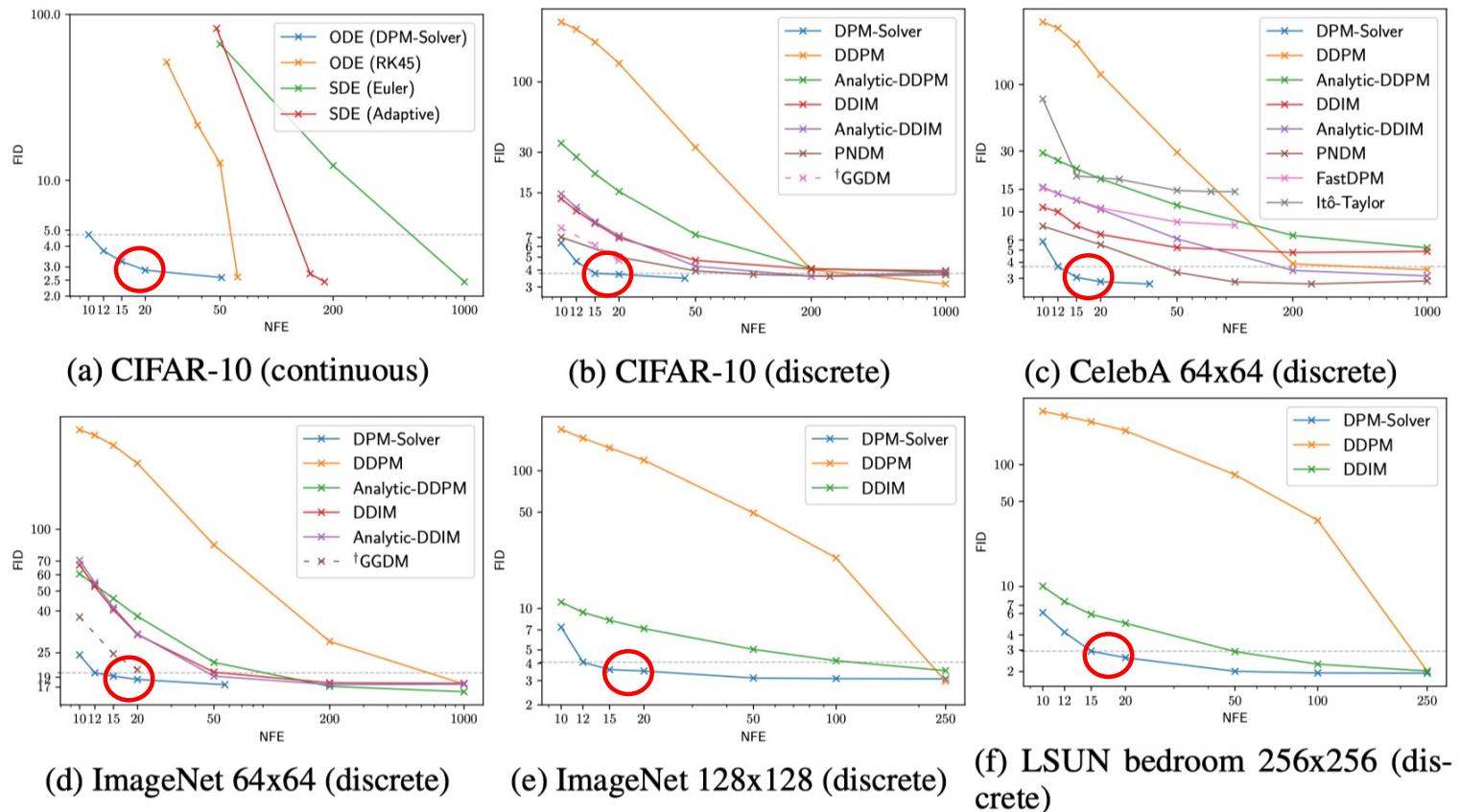
神经网络部分差分近似

解析形式

高阶小量



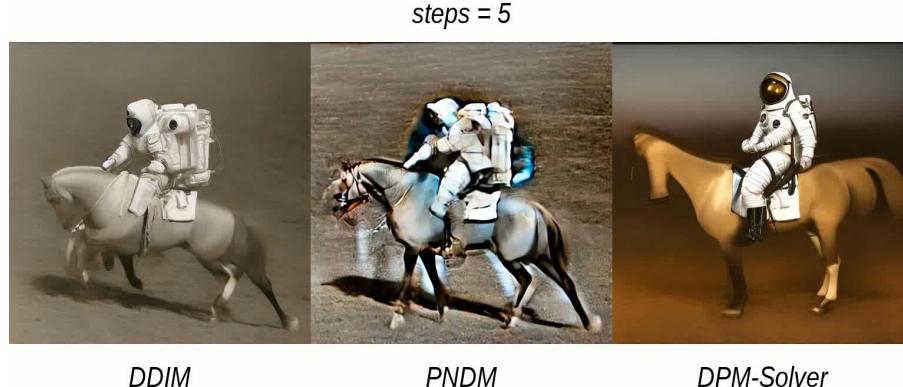
DPM-Solver: 结果



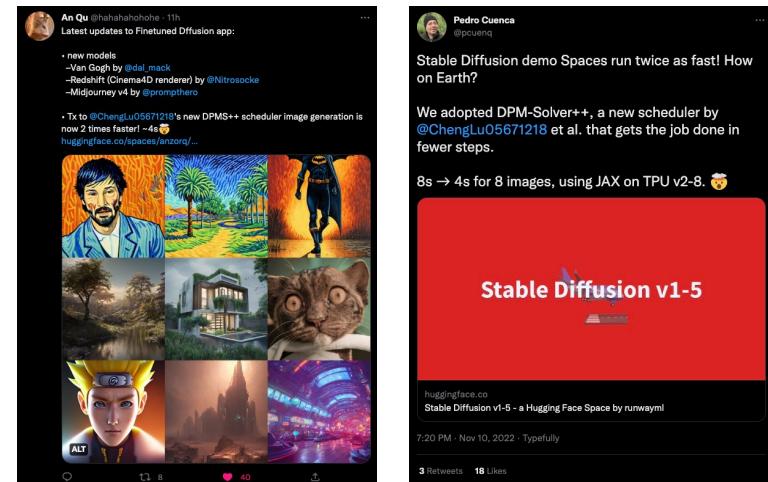


DPM-Solver: 结果

- 是当前最快的无需额外学习的扩散概率模型采样算法，**15步生成高清图像**
- 被多个主流开源社区（Github 累计星标 6万余次）支持/设为默认算法



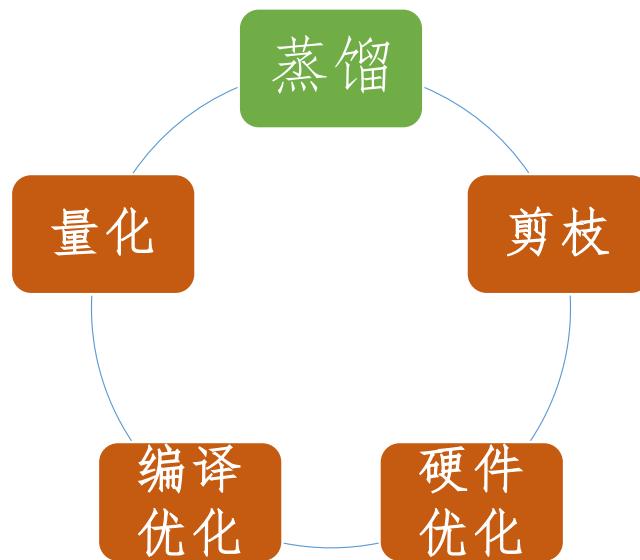
根据文本输入 15 步生成 512x512 高清图
像



著名开源模型 **Stable Diffusion** 等官方宣传⁶³

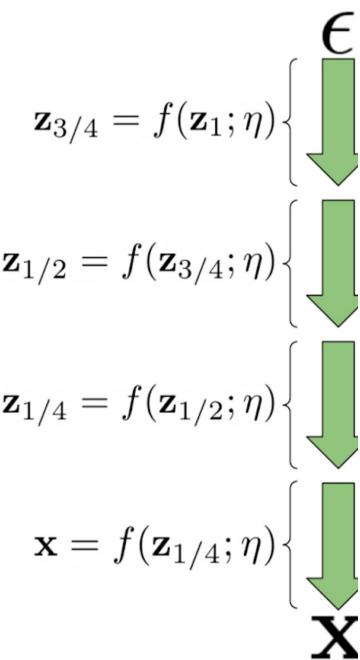


从深度学习模型加速的视角出发



Progressive Distillation

$t = 1$



$t = 0$

Distillat

Algorithm 2 Progressive distillation

```

Require: Trained teacher model  $\hat{\mathbf{x}}_\eta(\mathbf{z}_t)$ 
Require: Data set  $\mathcal{D}$ 
Require: Loss weight function  $w()$ 
Require: Student sampling steps  $N$ 
for  $K$  iterations do
     $\theta \leftarrow \eta$                                  $\triangleright$  Init student from teacher
    while not converged do
         $\mathbf{x} \sim \mathcal{D}$ 
         $t = i/N, i \sim \text{Cat}[1, 2, \dots, N]$ 
         $\epsilon \sim N(0, I)$ 
         $\mathbf{z}_t = \alpha_t \mathbf{x} + \sigma_t \epsilon$ 
        # 2 steps of DDIM with teacher
         $t' = t - 0.5/N, t'' = t - 1/N$ 
         $\mathbf{z}_{t'} = \alpha_{t'} \hat{\mathbf{x}}_\eta(\mathbf{z}_t) + \frac{\sigma_{t'}}{\sigma_t} (\mathbf{z}_t - \alpha_t \hat{\mathbf{x}}_\eta(\mathbf{z}_t))$ 
         $\mathbf{z}_{t''} = \alpha_{t''} \hat{\mathbf{x}}_\eta(\mathbf{z}_{t'}) + \frac{\sigma_{t''}}{\sigma_{t'}} (\mathbf{z}_{t'} - \alpha_{t'} \hat{\mathbf{x}}_\eta(\mathbf{z}_{t'}))$ 
         $\tilde{\mathbf{x}} = \frac{\mathbf{z}_{t''} - (\sigma_{t''}/\sigma_t) \mathbf{z}_t}{\alpha_{t''} - (\sigma_{t''}/\sigma_t) \alpha_t}$                                  $\triangleright$  Teacher  $\hat{\mathbf{x}}$  target
         $\lambda_t = \log[\alpha_t^2/\sigma_t^2]$ 
         $L_\theta = w(\lambda_t) \|\tilde{\mathbf{x}} - \hat{\mathbf{x}}_\theta(\mathbf{z}_t)\|_2^2$ 
         $\theta \leftarrow \theta - \gamma \nabla_\theta L_\theta$ 
    end while
     $\eta \leftarrow \theta$                                  $\triangleright$  Student becomes next teacher
     $N \leftarrow N/2$                                  $\triangleright$  Halve number of sampling steps
end for

```

提前确定noise schedule

基于预训练模型，以确定性

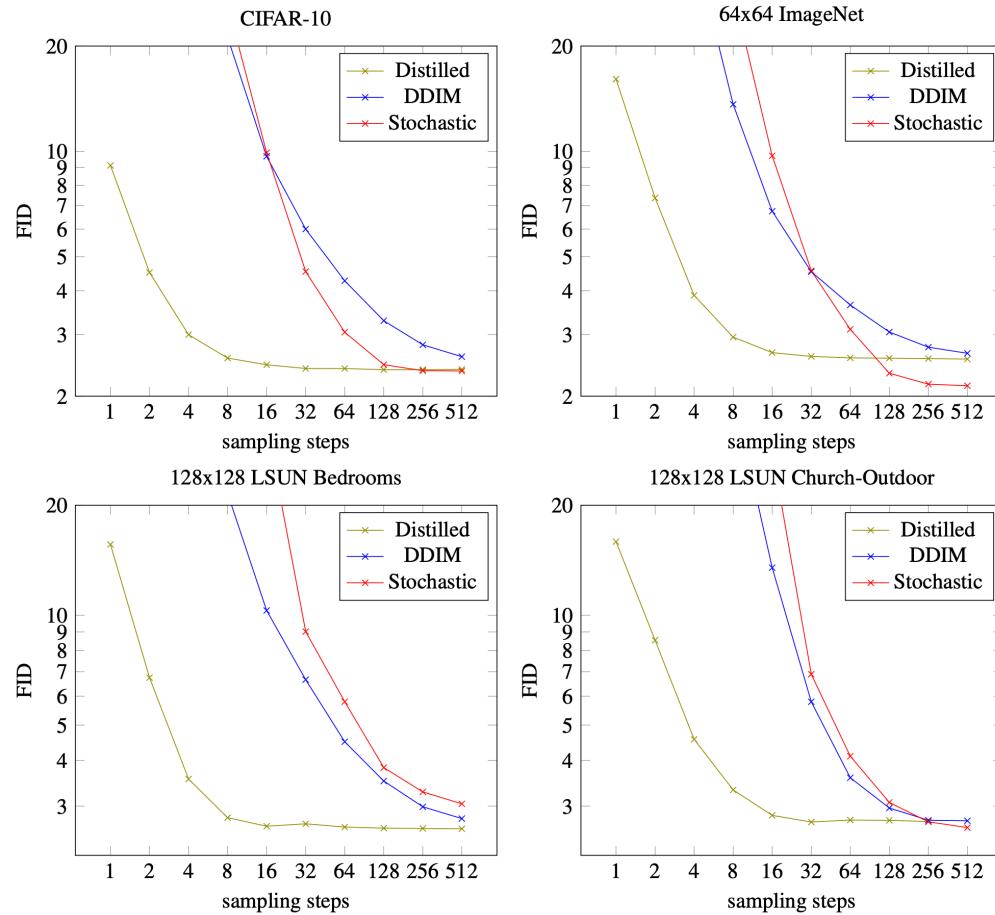
ODE sampler作为教师

2步蒸馏为1步： 学生只需要
教师的一半采样步

循环往复



Progressive Distillation: 结果



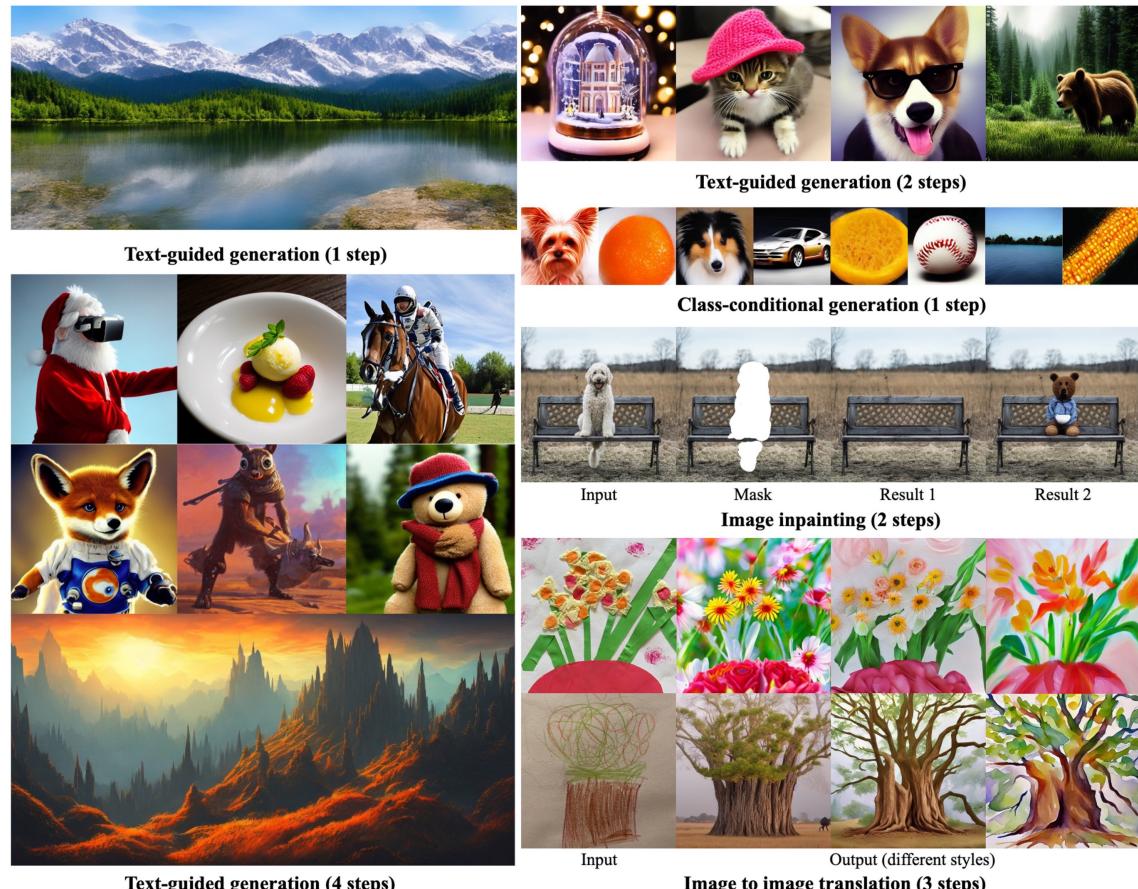
在不显著影响生成质量的情况下，
将需要的采样步降低到4：

- CIFAR-10 上 FID: 3.0



改进：On Distillation of Guided Diffusion Models (Meng et al., CVPR 2023)

- 带来了：
 - CF-Guidance
 - Stochastic sampling
 - Text-to-image
 - Image-to-image
 - Inpainting
 - Latent Diffusion



1-4步即可生成高质量大图



蒸馏的终极目标：一步生成

Consistency Distillation

- 概率流ODE定义了从噪声到数据的一一映射
=>直接建模此映射

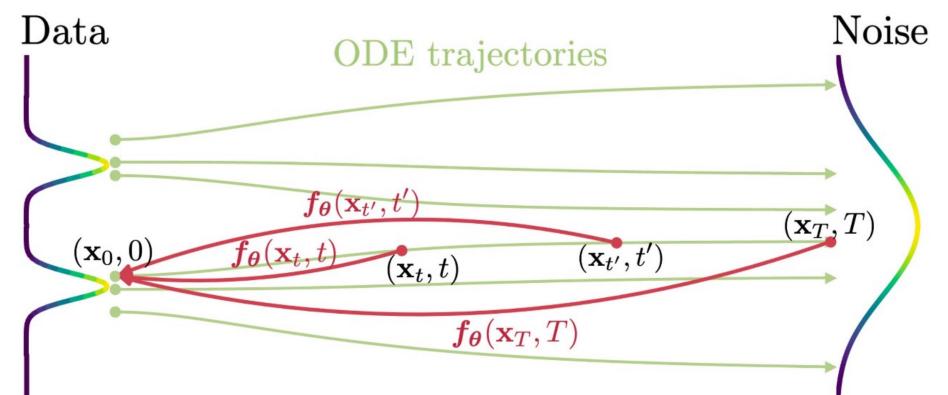
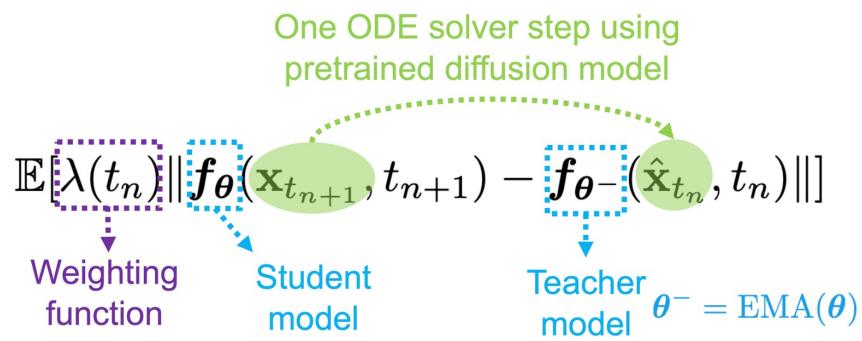
$$\forall t \in [0, T] : f_{\theta}(\mathbf{x}_t, t) = \mathbf{x}_0$$

- 模型参数化：需保证边界条件 ($t=0$)

$$f_{\theta}(\mathbf{x}, t) = c_{\text{skip}}(t)\mathbf{x} + c_{\text{out}}(t)F_{\theta}(\mathbf{x}, t)$$

$$c_{\text{skip}}(0) = 1 \quad c_{\text{out}}(0) = 0$$

- 训练：



Algorithm 1 Multistep Consistency Sampling

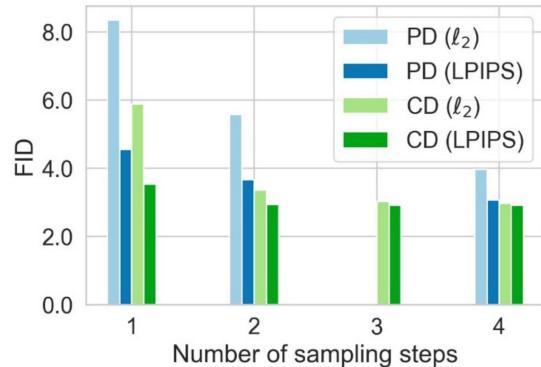
```

Input: Consistency model  $f_{\theta}(\cdot, \cdot)$ , sequence of time points  $\tau_1 > \tau_2 > \dots > \tau_{N-1}$ , initial noise  $\hat{\mathbf{x}}_T$ 
 $\mathbf{x} \leftarrow f_{\theta}(\hat{\mathbf{x}}_T, T)$ 
for  $n = 1$  to  $N - 1$  do
    Sample  $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
     $\hat{\mathbf{x}}_{\tau_n} \leftarrow \mathbf{x} + \sqrt{\tau_n^2 - \epsilon^2} \mathbf{z}$ 
     $\mathbf{x} \leftarrow f_{\theta}(\hat{\mathbf{x}}_{\tau_n}, \tau_n)$ 
end for
Output:  $\mathbf{x}$ 

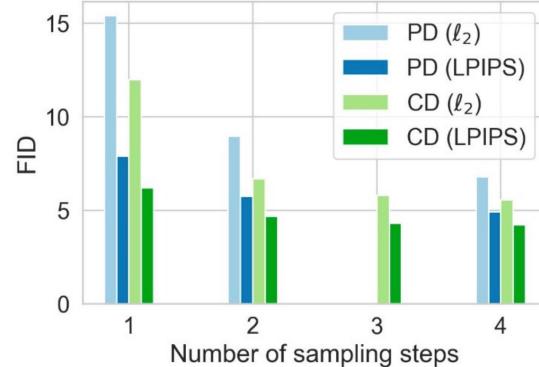
```



Consistency Distillation: 结果



(a) CIFAR-10



(b) ImageNet 64×64

一步生成的**SOTA** FID:

- 3.55 on CIFAR-10
- 6.20 on ImageNet 64

可用于零样本图
像编辑等应用



(a) Left: The gray-scale image. Middle: Colorized images. Right: The ground-truth image.



(b) Left: The downsampled image (32×32). Middle: Full resolution images (256×256). Right: The ground-truth image (256×256).



(c) Left: A stroke input provided by users. Right: Stroke-guided image generation.



Consistency Distillation: 用于DALL-E 3



In a fantastical setting, a highly detailed furry humanoid skunk with piercing eyes confidently poses in a medium shot, wearing an animal hide jacket. The artist has masterfully rendered the character in digital art, capturing the intricate details of fur and clothing texture.



A illustration from a graphic novel. A bustling city street under the shine of a full moon. The sidewalks bustling with pedestrians enjoying the nightlife. At the corner stall, a young woman with fiery red hair, dressed in a signature velvet cloak, is haggling with the grumpy old vendor. the grumpy vendor, a tall, sophisticated man is wearing a sharp suit, sports a noteworthy moustache is animatedly conversing on his steampunk telephone.



隐空间的Consistency Distillation

适用于蒸馏SD

$$\text{参数化: } \mathbf{f}_{\theta}(\mathbf{z}, \mathbf{c}, t) = c_{\text{skip}}(t)\mathbf{z} + c_{\text{out}}(t) \left(\frac{\mathbf{z} - \sigma_t \hat{\epsilon}_{\theta}(\mathbf{z}, \mathbf{c}, t)}{\alpha_t} \right), \quad (\epsilon\text{-Prediction})$$

Algorithm 1 Latent Consistency Distillation (LCD)

Input: dataset \mathcal{D} , initial model parameter θ , learning rate η , ODE solver $\Psi(\cdot, \cdot, \cdot, \cdot)$, distance metric $d(\cdot, \cdot)$, EMA rate μ , noise schedule $\alpha(t)$, $\sigma(t)$, guidance scale $[w_{\min}, w_{\max}]$, skipping interval k , and encoder $E(\cdot)$

Encoding training data into latent space: $\mathcal{D}_z = \{(\mathbf{z}, \mathbf{c}) | \mathbf{z} = E(\mathbf{x}), (\mathbf{x}, \mathbf{c}) \in \mathcal{D}\}$ 引入跳跃步数, 但ODE solver走一步
 $\theta^- \leftarrow \theta$

repeat

 Sample $(\mathbf{z}, \mathbf{c}) \sim \mathcal{D}_z$, $n \sim \mathcal{U}[1, N - k]$ and $\omega \sim [\omega_{\min}, \omega_{\max}]$

 Sample $\mathbf{z}_{t_{n+k}} \sim \mathcal{N}(\alpha(t_{n+k})\mathbf{z}; \sigma^2(t_{n+k})\mathbf{I})$

$\hat{\mathbf{z}}_{t_n}^{\Psi, \omega} \leftarrow \mathbf{z}_{t_{n+k}} + (1 + \omega)\Psi(\mathbf{z}_{t_{n+k}}, t_{n+k}, t_n, \mathbf{c}) - \omega\Psi(\mathbf{z}_{t_{n+k}}, t_{n+k}, t_n, \emptyset)$ 引入CFG

$\mathcal{L}(\theta, \theta^-; \Psi) \leftarrow d(\mathbf{f}_{\theta}(\mathbf{z}_{t_{n+k}}, \omega, \mathbf{c}, t_{n+k}), \mathbf{f}_{\theta^-}(\hat{\mathbf{z}}_{t_n}^{\Psi, \omega}, \omega, \mathbf{c}, t_n))$ 输入更多参数

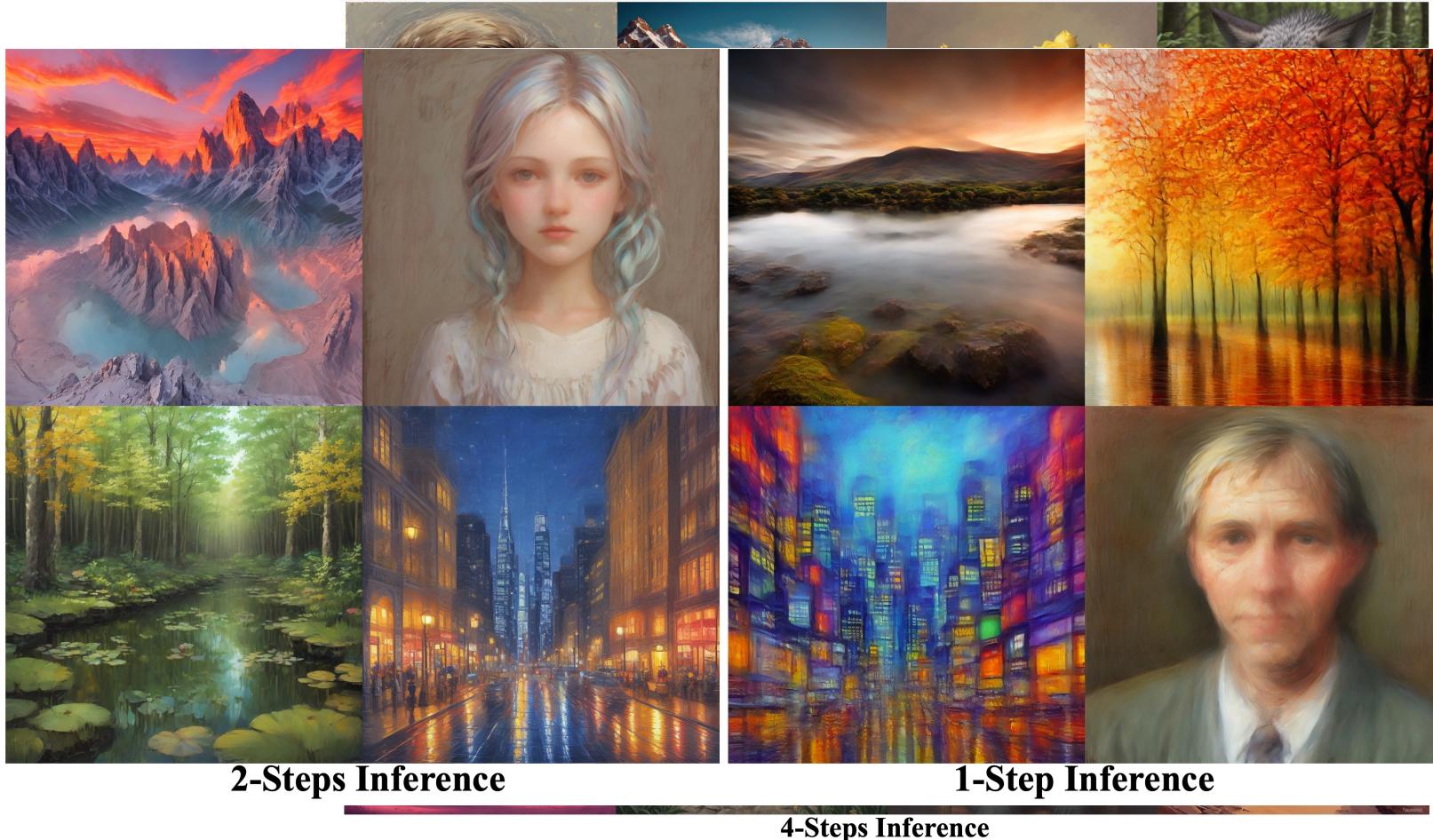
$\theta \leftarrow \theta - \eta \nabla_{\theta} \mathcal{L}(\theta, \theta^-)$

$\theta^- \leftarrow \text{stopgrad}(\mu\theta^- + (1 - \mu)\theta)$

until convergence



隐空间的Consistency Distillation



从预训练SD蒸馏：

- 4,000个训练步
(约32个A100 GPU hour)
- 生成高质量的
768×768分辨率
图像



对抗性扩散蒸馏

学生只学习4个
时间步上的去噪

$$s \in T_{\text{student}} = \{\tau_1, \dots, \tau_n\}$$

$$t \in T_{\text{teacher}} = \{1, \dots, 1000\}$$

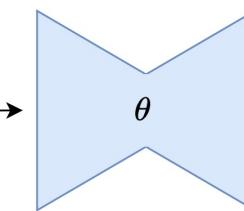
$$\epsilon, \epsilon' \sim \mathcal{N}(0, [I])$$

$d(x, y)$ distance metric e.g. $\|x - y\|_2^2$

forward diffusion process



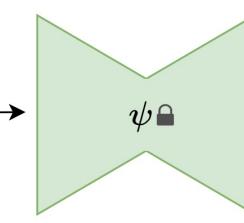
$$x_s = \alpha_s x_0 + \sigma_s \epsilon$$



ADD-student



$$\hat{x}_{\theta, t} = \alpha_t \hat{x}_\theta + \sigma_t \epsilon'$$

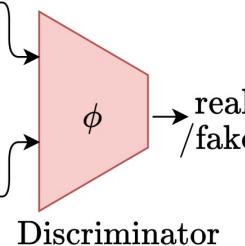


DM-teacher



真实数据定
义的先验

adversarial loss



distillation loss

$$c(t) d(\hat{x}_\theta, \hat{x}_\psi)$$

stop grad

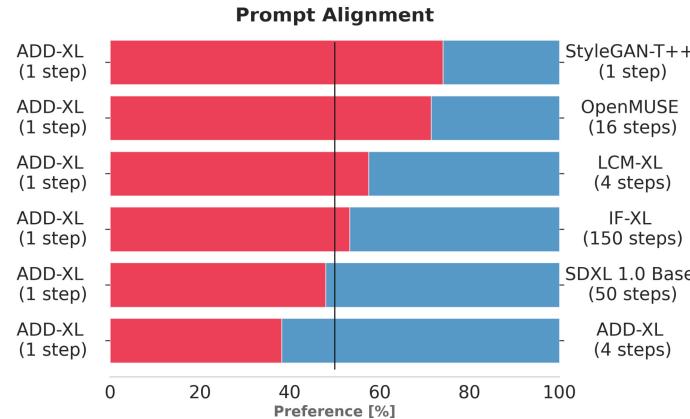
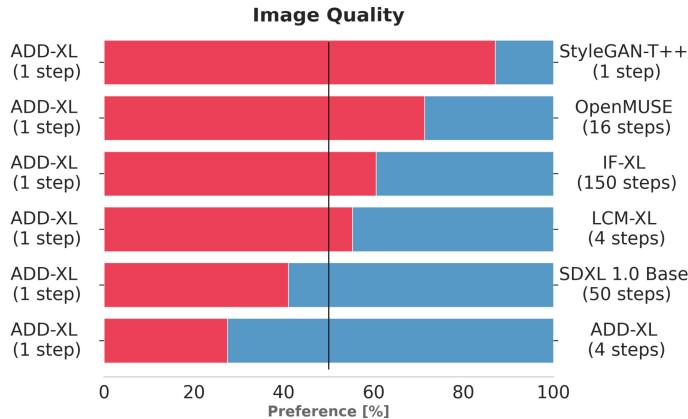
预训练SD定
义的先验

学习Stylegan-t，设计
判别器的结构和损失

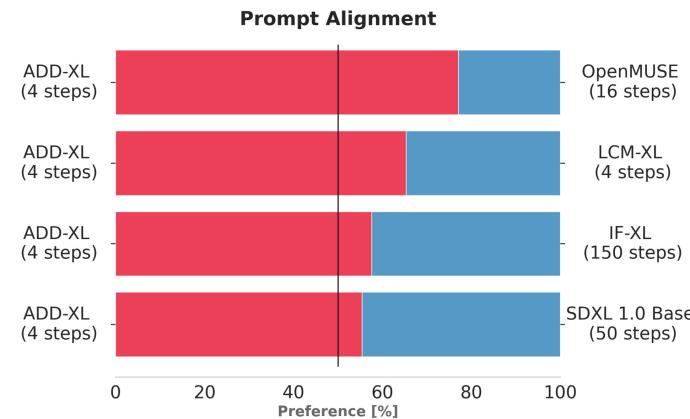
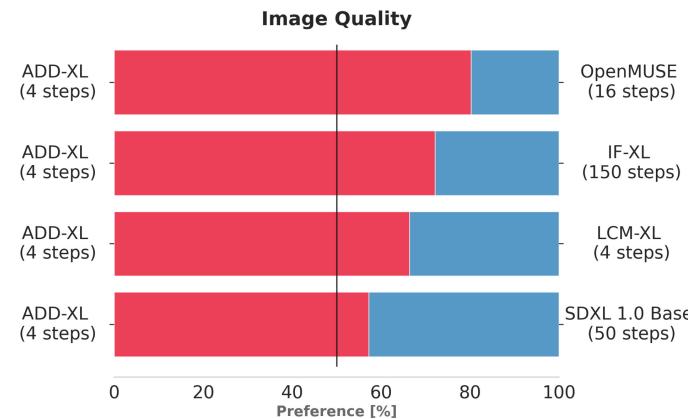
化简后和2D-3D
蒸馏的SDS loss
基本一样



对抗性扩散蒸馏：结果



真实用户偏好结果：
1-4步均优于StyleGAN-T++、LCM-XL、
SDXL



在4步的情况下，ADD-XL甚至超越教师模型
SDXL-Base



对抗性扩散蒸馏：1步生成结果





对抗性扩散蒸馏：2-4步生成结果

“A brain riding a rocketship heading towards the moon.”



“A bald eagle made of chocolate powder, mango, and whipped cream”



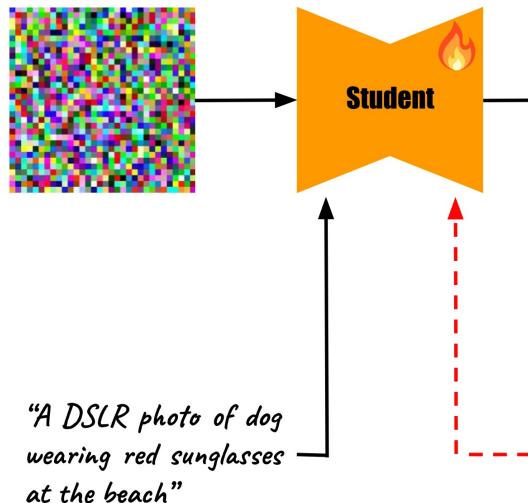
“A blue colored dog.”



局限：不能超过4步



SwiftBrush: VSD替换SDS、不需要对抗损失



Algorithm 1 SwiftBrush Distillation

```

1: Require: a pretrained text-to-image teacher  $\epsilon_\psi$ , a
   LoRA teacher  $\epsilon_\phi$ , a student model  $f_\theta$ , two learning rates
    $\eta_1$  and  $\eta_2$ , a weighting function  $\omega$ , a prompts dataset
    $Y$ , the maximum number of time steps  $T$  and the noise
   schedule  $\{(\alpha_t, \sigma_t)\}_{t=1}^T$  of the teacher model
2: Initialize:  $\phi \leftarrow \psi, \theta \leftarrow \psi$ 
3: while not converged do
4:   Sample input noise  $z \sim \mathcal{N}(0, I)$ 
5:   Sample text caption input  $y \sim Y$ 
6:   Compute student output  $\hat{x}_0 = f_\theta(z, y)$ 
7:   Sample timestep  $t \sim \mathcal{U}(0.02T, 0.98T)$ 
8:   Sample added noise  $\epsilon \sim \mathcal{N}(0, I)$ 
9:   Compute noisy sample  $\hat{x}_t = \alpha_t \hat{x}_0 + \sigma_t \epsilon$ 
10:   $\theta \leftarrow \theta - \eta_1 [\omega(t) (\epsilon_\psi(\hat{x}_t, t, y) - \epsilon_\phi(\hat{x}_t, t, y)) \frac{\partial \hat{x}_0}{\partial \theta}]$ 
11:  Sample timestep  $t' \sim \mathcal{U}(0, T)$ 
12:  Sample added noise  $\epsilon' \sim \mathcal{N}(0, I)$ 
13:  Compute noisy sample  $\hat{x}_{t'} = \alpha_{t'} \hat{x}_0 + \sigma_{t'} \epsilon'$ 
14:   $\phi \leftarrow \phi - \eta_2 \nabla_\phi \|\epsilon_\phi(\hat{x}_{t'}, t', y) - \epsilon'\|^2$ 
15: end while
16: return trained student model  $f_\theta$ 

```

$$\min_{\epsilon_\phi} \mathbb{E}_{t,c,\epsilon} \|\epsilon_\phi(x_t, t, y, c) - \epsilon\|_2^2$$

$$-\mathcal{L}_{\text{diff}}$$

矣为预测teacher的输出

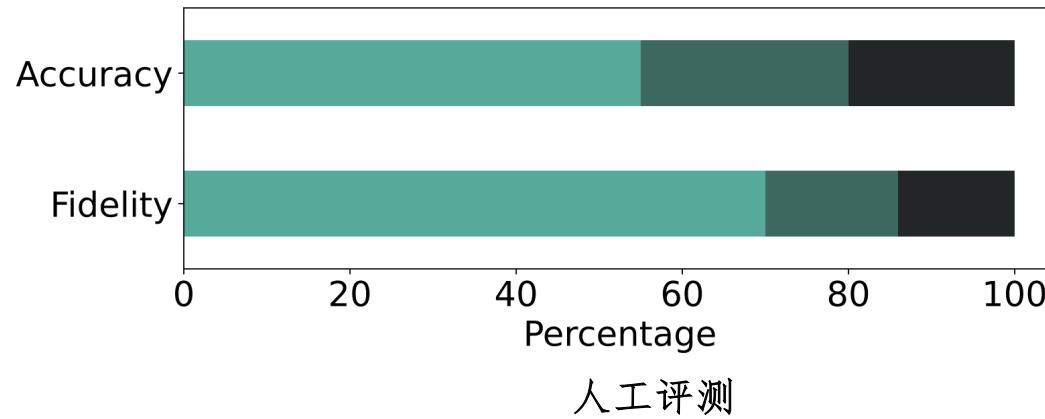
$$-\mathcal{L}_{\text{VSD}}$$

$$\mathcal{S}_D = \mathbb{E}_{t,\epsilon,c} [w(t)(\epsilon_\psi(x_t, t, y)$$

$$- \epsilon_\phi(x_t, t, y, c)) \frac{\partial g(\theta, c)}{\partial \theta}]$$



SwiftBrush：结果



综合来看可能不如ADD，侧面反映了对抗的重要性

Method	Steps	FID-30K ↓	CLIP-30K ↑
Guided Distillation [†]	1	37.3	0.27
LCM [†]	1	35.56	0.24
Instafow	1	13.10[†]	<u>0.28[§]</u>
BOOT [‡]	1	48.20	0.26
Ours	1	<u>16.67</u>	0.29
SD 2.1*	25	13.45	0.23
SD 2.1*	1	202.14	0.06

COCO 2014上的量化指标



SwiftBrush：1步生成结果



Nguyen & Tran. SwiftBrush : One-Step Text-to-Image Diffusion Model with Variational Score Distillation.



报告总结

- 扩散模型的理论和方法基础
 - 隐变量模型 vs. 评分函数估计
 - 无限时间步的扩展
 - 网络结构: **U-Net vs. U-ViT**
- 扩散模型的方法研究: 更可靠、普适、高效
 - 基础改进
 - 对预训练分数预测模型的完善、校准、增强
 - 面向更高分辨率、多模态
 - 生成加速
 - 设计**ODE Solver**
 - 模型蒸馏、一致性模型

感谢各位专家！敬请批评指正！

邮箱：zhijied@sjtu.edu.cn

主页：<https://thudzj.github.io/>



Github